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Abstract

Uddanam, Srikakulam in Andhra Pradesh, a conglomeration of an apportioned group of villages, grapples with a severe and mysterious kidney disease epidemic since the 1980s, affecting agricultural communities. The region, which was once fondly called "Udyanam," translated as "Garden," for its richness in greenery and cashew and coconut trees, has now become "Uddanam," the land of death and despair. The residents of the region suffer with high rates of kidney failure and associated health complications for factors including environmental toxins and poor water quality. Despite several efforts by governments, the impact of governmental policy on improving the conditions has been non-significant. The problem has been taken into sincere and serious consideration by the present Government of Andhra Pradesh which introduced ground breaking welfare initiatives to impede the prevalence of the disease and the deaths among patients. This paper presents an analytic report, with precise scientific rigor, the positive impact of the government's welfare schemes, and the areas that need urgent public policy intervention. This paper is the first to identify, that out of the total of 942 CKD patients interviewed uniformly at random from the Uddanam mandalas, a majority of 86.06%, who belong to advanced stages, receive advanced govern- mental (free) medical care, and soon succumb to the disease, and a minority of 13.94%. who belong to early stages of the disease, do not benefit directly from government welfare schemes, and hence perpetually proceed to advanced stages. This paper also proposes health and public policy measures to overcome this challenge.

Keywords: Chronic kidney disease, Uddanam, government welfare schemes, free dialysis, public health policy, society

1 Introduction

The Uddanam region in the Srikakulam district of Andhra Pradesh, India, has gained significant attention in recent years due to the high prevalence of chronic kidney dis- ease (CKD) among its residents. The region has been identified as one of the global hot spots for CKD of unknown origin (CKDu), characterized by its disproportionate impact on agricultural communities. The multi-factorial etiology of CKD in Uddanam, including environmental, occupational, and socio-economic factors, presents complex challenges for disease management and prevention. Understanding the epidemiology and risk factors associated with CKD in Uddanam is crucial for designing targeted interventions and healthcare policies to mitigate its impact on affected communities. Furthermore, investigating the genetic, environmental, and lifestyle factors contributing to the high prevalence of CKD in Uddanam can provide valuable insights into the broader implications of kidney disease on a global scale. Efforts to address the CKD epidemic in Uddanam require a multidisciplinary approach, involving collaboration between healthcare professionals, researchers, policymakers, and community stakeholders. By elucidating the significance of Uddanam Srikakulam in the context of CKD research, this paper underscores the ambivalent impact of the Andhra Pradesh Government schemes in mitigating its prevalence in the region and the public health interventions and research initiatives aimed at addressing the underlying determinants of kidney disease in affected populations. The rest of the paper is organised as follows. Section 2 presents the historical perspective of CKD, its prevalence in Uddanam villages, relevant research, and the government initiatives to counter the same. Section 3 sets the motivation for the survey and dis- cusses the preliminaries and the methods thereof. Section 4 presents the ambivalent impact of the current government schemes on the CKD patients of Uddanam. This is followed by the proposal of public policy measures to counter the identified snags in section 5 and the concluding remarks in section 6.

2 Historical perspective and related work

The historical aspect of the CKD in Uddanam, Srikakulam, dates back several decades, with reports of kidney related health issues emerging as early as the 1980s [1, 2]. However, the prevalence of CKD gained significant attention in the early 2000s when it was recognized as a widespread health crisis affecting a large portion of the population, particularly in the agricultural communities of Uddanam. The condition was characterized by a high incidence of kidney failure and related complications among residents [3], leading to a substantial burden on healthcare resources and significant socio-economic impacts on affected families. The historical aspect of CKD in Uddanam is marked by the gradual recognition of its scale and severity over time. Several factors have been proposed as potential contributors to the development of CKD in Uddanam, including environmental toxins, poor water quality, agricultural chemicals, and socio-economic factors such as poverty and lack of access to healthcare [4]. The historical context of CKD in Uddanam underscores the complexity of the disease and the challenges associated with identifying its underlying causes. Over the years, various governmental and non-governmental organisations have initiated efforts to address the CKD crisis in Uddanam [5]. The first fruits of these initiatives along with the most rigorous government schemes proposed in the past three years are now bearing in the leadership of Hon. Chief Minister, Government of Andhra Pradesh, for initiatives including health screening programs, research studies, infrastructure development, subsidies, and public awareness campaigns. This paper aims to bring to light the two-sided impact of these initiatives in the past three years.

The Uddanam, Srikakulam is so plagued by the disease that nearly 30% of the total population suffers from the disease [6, 7]. The majority of the research outcome on the CKD problem of Uddanam, Srikakulam is focused on testing the quality of ground water and establishing the cause for the disease [8–11]. There has been strong experimental evidence that concludes that the presence of high levels of heavy metals including cadmium in the ground water and the extensive use of pesticides is a general cause for the prevalence of CKD [12]. Other work includes detecting specific gene variants that cause a high risk of prevalence of CKD [13]. Despite the extensive research, the disease continues to plague the region. Although the research into the cause and effect of the CKD in Uddanam is extensive and exhaustive, there is less work on the relevant public health and policy measures. For example, several governmental health and welfare schemes have been proposed for CKD patients in Uddanam in the context of their socio-economic standards, including free dialysis, health awareness camps, free medication, etc. in [14, 15]. There have been propositions to include community engagement and public inclusion policy for effective tackling of the situation by the governments [16]. Based on the fact that research into the etiology of CKD is still underway, there is an increased need for more public policy initiatives to impede its effect on the residents [17]. The uncontrolled prevalence of the diseased called for development of sophisticated research cum health centres (hospitals) that co-jointly conduct research and also provide quality treatment to the patients. To this effect, the Government of Andhra Pradesh instituted the YSR Sujaladhara Uddanam Drinking Water Project [18] in collaboration with Megha Engineering to promote the use of purified minieral water over ground water. The water is supplied at subsidized prices and residents are strongly encouraged to stop drinking ground water.

Several research agencies and institutions have been involved in studying chronic kidney disease in Uddanam, Srikakulam. Some of these include (a) the Indian Council of Medical Research (ICMR) for conducting epidemiological studies and research projects to understand the prevalence, etiology, and risk factors associated with CKD,

(b) the National Institute of Nutrition (NIN) [19] for conducting research on the nutritional aspects and dietary factors related to CKD in Uddanam, (c) Achutha Menon Centre for Health Science Studies (AMCHSS) for studies focusing on the epidemiology and public health aspects of CKD in Uddanam, and (d) the Andhra University [20] for conducting collaborative studies on genetic predisposition and public policy. The prevalence of Uddanam was instrumental in evolving “hospitals” into “research hospitals”, research hospitals including the KIMS-ICON kidney research foundation, the Apollo hospitals, Government hospitals and diagnostic centers and the recently established Dr. YSR Kidney Research Centre and Super Specialty Hospital, Palasa, actively collaborate with local healthcare providers, government bodies, and international organizations to conduct multidisciplinary research and provide quality medical care to CKD patients [21]. The government has initiated several welfare schemes, in addition to the research medical facilities, including Arogyasri, free dialysis, free medication and monetary benefit of INR 10,000 (Rupees Ten Thousand) per month, to intersect the benefits of medical care and governmental assistance. A precise ambivalent analytic conclusion of the impact of the said initiatives in the past three years is not available to date. The next section presents the details of the survey.

3 Survey details

This section first presents the motivation for the survey and then the data preliminaries.

3.1 Motivation for the survey

The promulgation of research hospitals and welfare schemes in Uddanam in the current government's regime had positively impacted the lives of many CKD affected families in Uddanam. All hospitals and diagnostic centers have been upgraded with state-of- the-art facilities for dialysis. The Hon. Chief Minister of Andhra Pradesh recently opened the Dr. YSR Kidney Research Centre and Super Specialty Hospital, Palasa for specialized care of CKD patients. Moreover, the government also initiated a water supply plant, the YSR Sujaladhara Uddanam Drinking Water Project, in collaboration with Megha Engineering and Infrastructure Limited (MEIL) for a total budget of 700 crore rupees. The government topped the medical facilities with liberal welfare schemes in way of free dialysis and medication.

Defn. 3.1: Objective of the Government of Andhra Pradesh

In his inaugural speech of the opening of Dr. YSR Kidney Research Centre and Super Specialty Hospital, Hon. Chief Minister, Government of Andhra Pradesh said that the motto of the government is to ensure that no eligible soul in Uddanam should lose on the benefits of the government schemes.

In light of the sincere and serious efforts of the government in the past five years, a detailed statistical analysis of the positive, negative and missing aspects of govern- mental assistance in eradicating the prevalence of CKD and treating its victims is not available as a public article to date. This survey aims to fill the gap by statistically measuring the aforementioned objective of the Government of Andhra Pradesh and present the ambivalent impact of government schemes in terms of both medical and welfare assistance.

3.2 Survey preliminaries

The survey was conducted in 72 villages of the Srikakulam District, spanning several mandalas, namely, Palasa, Ichapuram, Kanchili, Sompeta, Kaviti, Mandasa and Vajrapu Kotturu, which have been seriously affected by the CKD. The data presented herein corresponds to our survey conducted over three months and culminated on 14-02-2024. During the survey, we have personally visited several medical facilities including the Government Hospital, Palasa, Dialysis Centre, Haripuram and the highly acclaimed Dr. YSR Kidney Research Centre and Super Specialty Hospital, Palasa recently inaugurated on 15-12-2023 by, Hon. Chief Minister, Government of Andhra Pradesh. The total number of CKD patients surveyed, i.e., the sample size, is 942, selected at absolute value[1] but randomly and uniformly from the aforementioned mandalas. Figure 1 shows the spatial distribution of the villages and medical centres visited to interview the CKD patients. The shown Uddanam region spans nearly 300 kilometers. The questionnaire and the raw statistical report are shown in Appendix A. In the sequel, we discuss the manifestation of CKD within the patients as a statistical characterization of their gender and the stage of the disease. We also discuss the statistical impact of the governmental schemes.

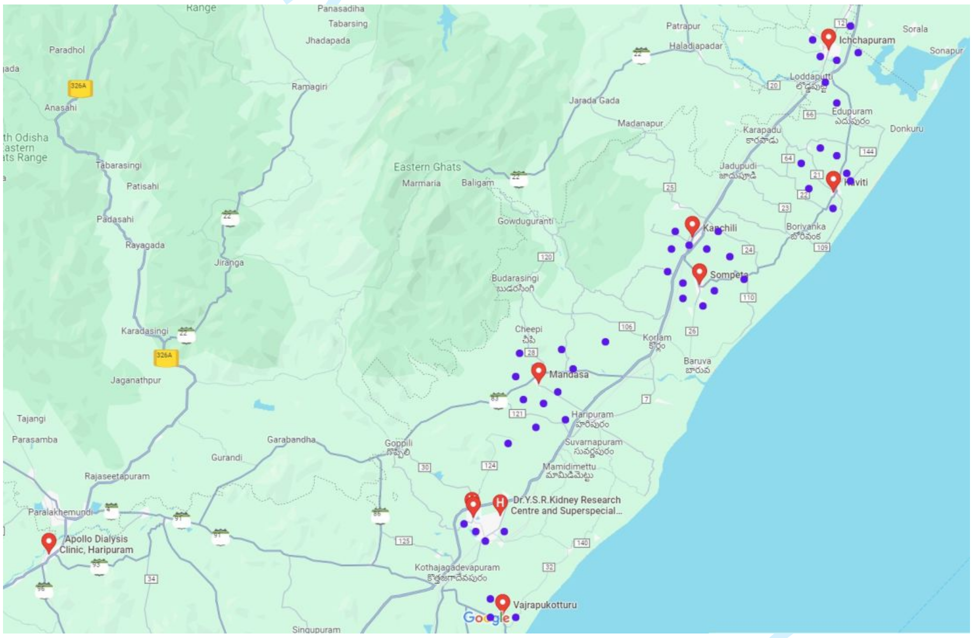


Fig. 1 The geographical distribution of the sample candidates surveyed, at random but uniformly from the aforementioned mandalas of Uddanam, Srikakulam.

[1]Absolute value means that all the 942 sample candidates are CKD patients.

4 The impact of government schemes

In this section, we present the key statistical features of the survey. Of the 942 individuals, 71% (669) are male and 29% (273) are female, shown in Figure 2. Nearly 81.8% of the total number of CKD patients surveyed are aged 45 years and more. Of the total sample size, 9.7% are in stage one, 35.15% in stage two, 41.21% in stage three, 2.42% in stage four and 11.52% in stage five. This is shown in Figure 3. The creatinine levels of CKD patients interviewed ranged from 0.9 to 10.0 which is indicative of the fact that a controlled value of the creatinine does not necessarily ensure perpetual
good health to the person. It has also been found that the progression of the severity of the CKD in both genders is synonymous with respect to both the sample size and the gender size. This trend can be observed in Figure 4. It can be observed that the proportion of people who advance to the final stages of the disease is higher in men than women. Women, on the other hand, who are a 1/3rd proportion of the total number of CKD infections, advance through stages one, two and three of the disease rapidly, but may not advance as much thereafter. This trend is in concurrence to the findings that the chances of the CKD advancing towards kidney failure are higher in men than women. A possible reason for this could be the presence of high testosterone and less estrogen [22].

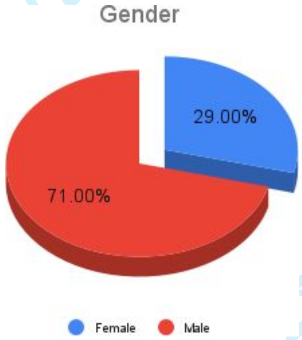


Fig. 2 The gender distribution of the total number of CKD patients interviewed.in Uddanam, Srikakulam.

Additionally, 67.8% of the people expressed their satisfaction about government reach to them through Asha workers, Village Volunteers and Gram Sachivalayam in aiding with respect to disease awareness and governmental assistance.
Based on the above findings, we infer that the number of people under 45 years of age who have been contracted with the CKD are only about 18% of the total sample size. This indicates that the number of CKD patients has seen a decreasing trend in the past three years as the Government of Andhra Pradesh has rigorously encouraged the use of purified mineral water over ground water. People are now being supplied with mineral water for a subsidized price

of nearly INR 5.00 (Rupees Five Only) or less for 40 liters can. The YSR Sujaladhara Uddanam Drinking Water Project has been instrumental in supplying fresh mineral water round the year irrespective of the weather conditions to all the villages affected by CKD. While supplying mineral water has reduced the proportion of CKD detection in the past three years, the government welfare schemes such as free dialysis, free medication for CKD affected patients has prolonged their lives. There are people who undergo free dialysis nearly thrice every week with a hope they shall live another day.

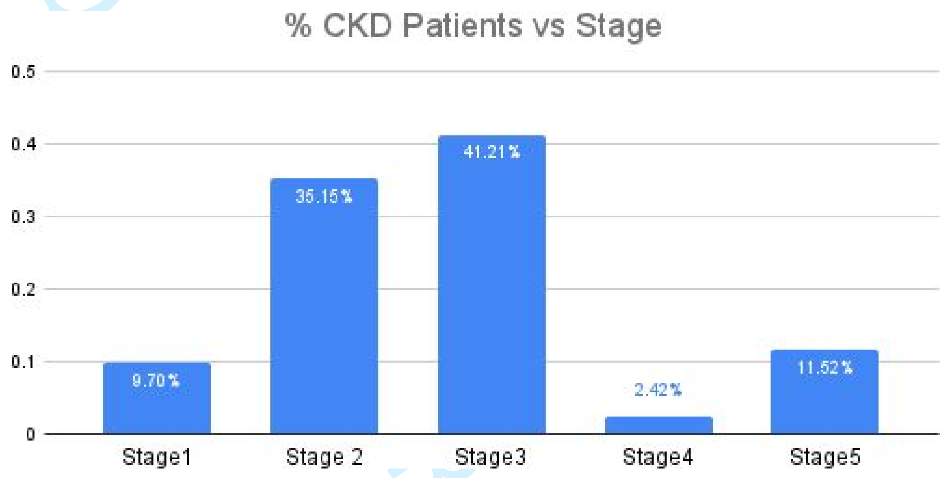


Fig. 3 The stage-wise distribution of the total number of CKD patients.

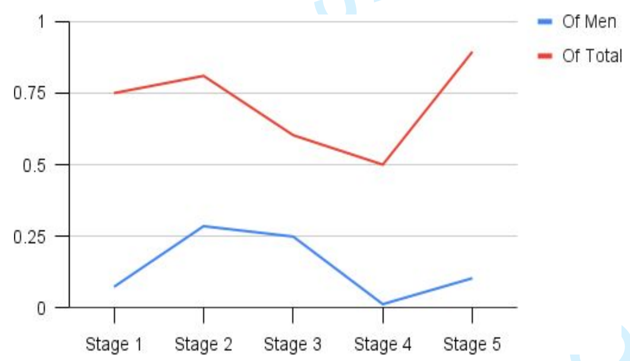
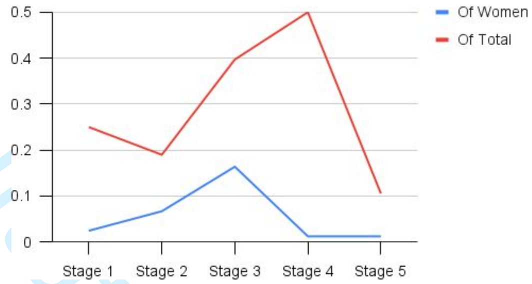


Fig. 4 The top panel shows the ratio of men affected with CKD with respect to the total sample size (red) and the total number of men (blue) as a function of the stage of the disease. The bottom panel shows the ratio of the women affected with CKD with respect to the total sample size (red) and the total number of women (blue) as a function of the stage of the disease.

4.1 Challenges

Despite the tremendous contribution of the government in providing medical care to current patients, there are certain aspects brought to light from our research survey that could create an impact in saving more lives than now. In this section, we present the data for the same. From our research survey, it has been surprisingly found that of the total sample size of 942 interviewed CKD patients, only 13.27% (125 Nos.) have recorded that they have



benefited directly from government welfare schemes while the remaining 86.73% (817 Nos.) recorded in the negative, as shown in Figure 5.

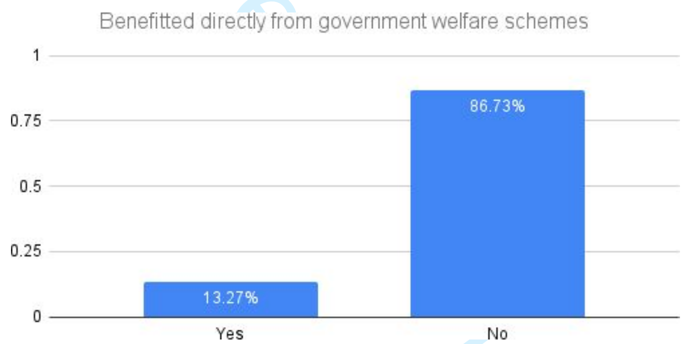


Fig. 5 The % of CKD patients who voted in positive and in negative for receiving benefit from the government as welfare schemes.

Of the 125 people who have benefited, 13.6% belong to stage four and the remain- ing 86.4% to stage five. There are no patients in stages one, two and three who have answered in the positive for having benefited from the government schemes. Of the 817 people who reportedly have not benefited, 11.18% belong to stage one, 40.55% to stage two, 47.55% to stage three and 0.06% to stage four. There are no patients in stage five. The said data is shown in Figure 6.

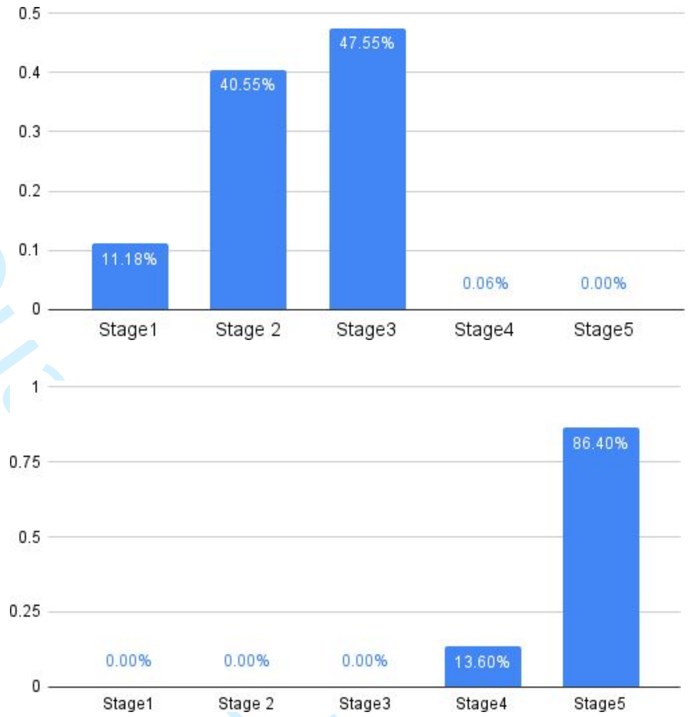


Fig. 6 The top panel shows the % of CKD patients who did not receive any government benefit versus the stage of the disease. The bottom panel shows the % of CKD patients who received any government benefit versus the stage of the disease.

This data has caused much surprise, to the extent that we did a second level survey by interviewing candidates randomly from among the both categories, which seconded the findings. As a concurrence for the above findings, when asked how the government could assist the CKD patients, 51.75% requested for advanced medication in early stages, 45.61% requested for more CKD awareness programs and the remain- ing requested for financial assistance for long travel. Moreover, almost all patients suggested that the medicines prescribed by the doctors are unavailable in the list of medicines provided for free by the government, and they are burdened by around INR 5,000 (Rupees Five Thousand) to INR 10,000 (Rupees Ten Thousand). This infers that CKD patients in stages four and five are the ones benefiting from government welfare schemes while those in stages one, two and three are reportedly not benefiting to their satisfaction from government schemes. As an indication of more concurrence to the finding, only 14.85% indicated that they have been personally benefited from government schemes, meaning that nearly 84% of the people, especially those belonging to stages one, two and three, have not received any perceivable government assistance. Moreover, as mentioned in section 4, nearly 67% of the people have received support directly through government health support staff, it is indeed a surprise that only 11% of the total candidates interviewed are benefiting from the use of digital technology for purposes including remote consultation, online verification of medical records, online reception of medical test results, online payments, etc.

It has been found that the people are used to receiving help in terms of governmental schemes, awareness, etc. through only governmental health workers who themselves are incapacitated to travel long distances and reach out stage 4 patients who should be isolated. The penetration of technology to rural population as this requires a deeper and stronger push from government and non-government agencies. This is in line with our discovery that only 2.27% of the people interviewed have good access to technology. The route to achieve higher digital penetration is through more physical awareness camps that reach the doorsteps of the people. When the final stage patients have been asked what best can be done at that stage, we have observed that most of them have made peace with themselves (which was an emotional ordeal for us) and 11\% of them requested for financial assistance to their spouses or children and most of them for financial aid to early-stage patients.

5 Key inferences and proposed policies

Based on the above findings, it could be inferred that the patients suffering from CKD stage three and four, for whom the creatinine levels would be in the range 5.0 to 10.0 and for whom the chances for survival are minuscule, are being provided the expensive dialysis cum medication treatment for free by the government. While this is commendable, the proportion of people benefited from this is only 13.94% of the total sample size. This perfectly corroborates that only 13.3% reported of having benefited directly from government welfare schemes. It is also the case that most of the people who benefit from free dialysis in their advanced stages of CKD eventually succumb to the disease. On the other hand, a large proportion of people, i.e., nearly 86.06% suffering from stage one, two and three of the CKD but not requiring any dialysis, are not benefiting in a major sense. This perfectly corroborates that a whopping 89.6% reported of having not benefited directly from government welfare schemes. That is to say, there is a great scope for the government to provide advanced medical facility for free to CKD patients in their early stages to increase their chances of survival. The key inferences of this paper are outlined as follows,

- The increased use of mineral water over ground water has caused a decreased record of the number of CKD cases in the past three years.

- The government reach to CKD patients through health workers and Sachivalayam have found much reach to the patients with respect to creating awareness about government welfare schemes.
- The free dialysis provided by the government to advanced stage CKD patients has been a boon by increasing their lifespan.
- The government welfare schemes are majorly benefiting patients who are in advanced stages of the disease. Despite the expensive dialysis and medication pro- vided for free by the government, these patients, in most cases, eventually succumb to the disease.
- There is an immediate need for government intervention and allocation of fund for welfare schemes for patients in their early stage of CKD so their progression towards advanced stage is decelerated, or prohibited.

Our research, as summarized above, has identified the positive impact and hope instilled by the Government of Andhra Pradesh in (a) deterring the prevalence of the disease by providing mineral water, and (b) providing advanced medical treatment to patients in advanced stages of the disease. As a first, this paper identifies the void in providing advanced medical care to patients in early stages of CKD as a statistical measure of their age, gender and stage of the disease. Therefore, there is an immediate need for providing advanced medical care to patients in early stages of their disease. From the survey, we observe the following, (a) it is critical to start advanced medication to patients in their early stages of the disease in order to impede the progression towards advanced stages, (b) it is also critical to ensure that the advanced medication prescribed by the doctors is available within the free medication list, (c) most importantly, the government should regulate the prescriptions of doctors to within the free medicines list and ensure private parties are not profited as the expense of a poor man's disease, (d) the number of super specialty hospitals is few for the wide range of Uddanam region and so the government should focus on providing free transport to patients or increasing the number of medical health outlets, (e) it is undoubtedly a surprise that fruit of digital technology has not reached the far corners of Uddanam, hence the government should take measures to increase the promulgation of the use of smart mobile phones by the patients for medical issues, and (f) the government should regularly organise awareness camps on the severity of the disease so even the slightest symptom of CKD will not go unnoticed. To summarise, this paper suggests the following public policy measures to be initiated by the government to overcome the challenges identified hitherto,

- Provide free medication and diagnostic facilities for continuous monitoring of creatinine for early-stage patients.
- Provide fully free public and private transport to CKD patients to visit the hospital regularly.

- Conduct regular awareness camps at the village level for patients and their families to understand the implications of CKD and the available governmental assistance.
- To promulgate the use of technology by giving free smartphones for receiving medical reports, consulting the doctor using web apps, etc.

6 Conclusion

This paper is the first to statistically measure the impact of medical and welfare schemes of the Government of Andhra Pradesh in prohibiting the prevalence of CKD in Uddanam villages and the treatment provided to its patients in the past three years. This paper primarily identified that the majority of the current government schemes are targeted towards free dialysis to patients who are in advanced stages of the disease while a minor proportion is allocated to those in their early stages. Public policy and health measures to address the problem are herein proposed in concurrence with the opportunities and challenges of the region. Additionally, this paper presented the reach of both the government and technology in reaching the people directly for medical benefit.

Declarations

- Funding: Not applicable.
- Conflict of interest/Competing interests (check journal-specific guidelines for which heading to use): The authors declare no conflict of interest.
- Ethics approval and consent to participate: Not applicable.
- Consent for publication: Not applicable.
- Data availability: Survey data is made available in raw format in Appendix A.
- Materials availability: Not applicable.
- Code availability: Not applicable.
- Author contribution

Appendix A Survey report

Personal Details

1. Gender
    - Male — 71%
    - Female — 29%
2. Age
    - < 18 years — 0.61%
    - 18-30 years — 3.64%
    - 31-45 years — 13.94%
    - 46-60 years — 47.88%
    - > 60 years — 33.94%
3. Occupation
    - Farmer — 40.13%
    - Agricultural laborer — 32.24%
    - Non-agricultural laborer — 23.68%
    - Others — 3.95%
4. Education level
    - No formal education — 49.70%
    - Primary school — 40.06%
    - Secondary school — 7.82%
    - College/University — 2.42%

Health Profile

1. Do you have any known kidney-related health issues?
    - Yes — 100%
    - No — 0%
2. Have you been diagnosed with chronic kidney disease (CKD)?
    - Yes — 100%
    - No — 0%
3. If yes, what stage of CKD have you been diagnosed with?

- Stage 1 — 9.7%
- Stage 2 — 35.15%
- Stage 3 — 41.21%
- Stage 4 — 2.42%
- Stage 5 — 11.52%

4. Do you have a family history of kidney disease?

- Yes — 3.13%
- No — 96.88%

5. What are the early symptoms of your disease?

- Swelling in your hands or feet — 55.56%
- Urinary Tract infections — 32.10%
- Blood in urine — 0.61%
- Kidney damage shown in scans — 11.73%

Lifestyle and habits

1. Do you consume well water for drinking purposes?

- Yes — 14.2%
- No — 85.8%

2. How many liters of water do you consume per day on average?

- < 1 — 49.08%
- 1-2 — 41.11%
- 2-3 — 7.36%
- > 3 — 2.45%

3. Do you consume alcohol?

- Yes — 93.94%
- No — 6.06%

4. Do you smoke tobacco or use any other forms of tobacco?

- Yes — 93.33%
- No — 6.67%

5. How often do you exercise per week?

- None — 83.64% (but they all work hard)

- 1-2 times — 16.4%
- 3-4 times — 0%
- 5 or more times — 0%

6. How often do you consume processed or fast food per week?

- Never — 29.7%
- Rarely — 62.42%
- Occasionally — 7.27%
- Frequently — 0.61%

Treatment, health care and awareness

1. Are you aware of chronic kidney disease and its symptoms?

- Yes — 64.42%
- No — 35.58%

2. Are you aware of any government health initiatives specifically aimed at addressing chronic kidney disease in your region, especially the Uddanam Kidney Hospital and Research Center?

- Yes — 62.96%
- No — 37.08%

3. If yes, please specify the initiatives you are aware of:

- Free dialysis — 91.18%
- Free medication — 2.50%
- INR 10,000 monetary benefit — 0.44%
- Government health worker support — 5.88%

4. How would you rate the effectiveness of government health programs in addressing CKD in your community?

- Very effective — 24.6%
- Not effective at all — 76.4%

5. Have you personally benefited from any government-sponsored healthcare services or programs related to CKD?

- Yes — 13.27%
- No — 86.73%

6. In your opinion, what further steps or measures should the state government take to address the issue of CKD effectively in your community?
    - Free medication — 51.75%
    - Awareness programs — 45.61%
    - Travel assistance — 2.64%
7. Have you received any awareness or information on preventing kidney disease from government healthcare professionals?
    - Yes — 54.09%
    - No — 45.91%

Financial impact

1. How would you describe the financial impact of managing CKD on your household in Uddanam?
    - Significant burden — 84.57%
    - Moderate burden — 6.17%
    - Minor burden — 9.26%
2. Which of the following expenses related to CKD have you or your family incurred in the past year in the Uddanam region?
    - Medications — 90.06%
    - Dialysis — 3.11%
    - Transportation to hospital — 6.83%
3. On average, how much do you spend on managing your CKD related expenses?
    - Less than INR 5,000 — 4.26%
    - 5,000 – 10,000 INR — 6.71%
    - 10,000 – 20,000 INR — 82.32%
    - More than 20,000 INR — 6.70%
4. Are you aware of any government subsidies or benefits available specifically for people affected by CKD in Uddanam?
    - Yes — 67.88%
    - No — 32.12%
5. If yes, which government subsidies are you aware of?
    - Financial Assistance to medical treatment — 4.2%

- Free dialysis — 95.80%
- Others — 0%

6. Have you or any of your family members benefited from any government subsidies related to CKD in Uddanam?

- Yes — 85.98%
- No — 14.02%

7. How would you rate the effectiveness of the state government in proactively treating the CKD affected people and helping manage related expenses?

- Excellent — 0.61%
- Good — 20.12%
- Somewhat good — 58.54%
- Poor — 20.73%

Technology

1. Do you use smartphone technology for matters related to CKD treatment including payment, health trackers, online medical reports, remote doctor consultation?

- Yes — 6.67%
- No — 93.33%

2. Do you support the use of recent technology in diagnosis and prognosis of CKD?

- Yes — 45.15%
- No — 54.85%

3. Have you been provided adequate training in use of technology for your medical needs?
   - Yes - 2.27%
   - No - 60.28%
   - Health worker does the job - 37.45%
4. Have you attended awareness camps on CKD?
   - Yes - 10.21%
   - No - 89.79%
5. What do you appreciate about the recent governmental attempts to provide superior medical care?
   - More medical health centers - 85.71%
   - Awareness camps - 12.21%
   - Technology penetration - 2.08%
6. What is the best help government can provide you, at this stage in your life?

- Financial support to family members after I pass away - 10.92%
- Financial support to early-stage patients - 60.95%
- More medical centers and easy access facilities - 28.13%

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The ambivalent impact of government schemes on chronic kidney disease patients in Uddanam, India: A qualitative study

Abstract

Uddanam, Srikakulam in Andhra Pradesh, a conglomeration of an apportioned group of villages, grapples with a severe and mysterious kidney disease epidemic since the 1980s, affecting agricultural communities. The region, which was once fondly called "Udyanam," translated as "Garden," for its richness in greenery and cashew and coconut trees, has now become "Uddanam," the land of death and despair. The residents of the region suffer with high rates of kidney failure and associated health complications for factors including environmental toxins and poor water quality. Despite several efforts by governments, the impact of governmental policy on improving the conditions has been non-significant. The problem has been taken into sincere and serious consideration by the present Government of Andhra Pradesh which introduced ground breaking welfare initiatives to impede the prevalence of the disease and the deaths among patients. This paper presents an analytic report, with precise scientific rigor, the positive impact of the government's welfare schemes, and the areas that need urgent public policy intervention. This paper is the first to identify, that out of the total of 942 CKD patients interviewed uniformly at random from the Uddanam mandalas, a majority of 86.06%, who belong to advanced stages, receive advanced govern- mental (free) medical care, and soon succumb to the disease, and a minority of 13.94%. who belong to early stages of the disease, do not benefit directly from government welfare schemes, and hence perpetually proceed to advanced stages. This paper also proposes health and public policy measures to overcome this challenge.

Keywords: Chronic kidney disease, Uddanam, government welfare schemes, free dialysis, public health policy, society

1 Introduction

The Uddanam region in the Srikakulam district of Andhra Pradesh, India, has gained significant attention in recent years due to the high prevalence of chronic kidney dis- ease (CKD) among its residents. The region has been identified as one of the global hot spots for CKD of unknown origin (CKDu), characterized by its disproportionate impact on agricultural communities. The multi-factorial etiology of CKD in Uddanam, including environmental, occupational, and socio-economic factors, presents complex challenges for disease management and prevention. Understanding the epidemiology and risk factors associated with CKD in Uddanam is crucial for designing targeted interventions and healthcare policies to mitigate its impact on affected communities. Furthermore, investigating the genetic, environmental, and lifestyle factors contributing to the high prevalence of CKD in Uddanam can provide valuable insights into the broader implications of kidney disease on a global scale. Efforts to address the CKD epidemic in Uddanam require a multidisciplinary approach, involving collaboration between healthcare professionals, researchers, policymakers, and community stakeholders. By elucidating the significance of Uddanam Srikakulam in the context of CKD research, this paper underscores the ambivalent impact of the Andhra Pradesh Government schemes in mitigating its prevalence in the region and the public health interventions and research initiatives aimed at addressing the underlying determinants of kidney disease in affected populations. The rest of the paper is organised as follows. Section 2 presents the historical perspective of CKD, its prevalence in Uddanam villages, relevant research, and the government initiatives to counter the same. Section 3 sets the motivation for the survey and dis- cusses the preliminaries and the methods thereof. Section 4 presents the ambivalent impact of the current government schemes on the CKD patients of Uddanam. This is followed by the proposal of public policy measures to counter the identified snags in section 5 and the concluding remarks in section 6.

2 Historical perspective and related work

The historical aspect of the CKD in Uddanam, Srikakulam, dates back several decades, with reports of kidney related health issues emerging as early as the 1980s [1, 2]. However, the prevalence of CKD gained significant attention in the early 2000s when it was recognized as a widespread health crisis affecting a large portion of the population, particularly in the agricultural communities of Uddanam. The condition was characterized by a high incidence of kidney failure and related complications among residents [3], leading to a substantial burden on healthcare resources and significant socio-economic impacts on affected families. The historical aspect of CKD in Uddanam is marked by the gradual recognition of its scale and severity over time. Several factors have been proposed as potential contributors to the development of CKD in Uddanam, including environmental toxins, poor water quality, agricultural chemicals, and socio-economic factors such as poverty and lack of access to healthcare [4]. The historical context of CKD in Uddanam underscores the complexity of the disease and the challenges associated with identifying its underlying causes. Over the years, various governmental and non-governmental organisations have initiated efforts to address the CKD crisis in Uddanam [5]. The first fruits of these initiatives along with the most rigorous government schemes proposed in the past three years are now bearing in the leadership of Hon. Chief Minister, Government of Andhra Pradesh, for initiatives including health screening programs, research studies, infrastructure development, subsidies, and public awareness campaigns. This paper aims to bring to light the two-sided impact of these initiatives in the past three years.

The Uddanam, Srikakulam is so plagued by the disease that nearly 30% of the total population suffers from the disease [6, 7]. The majority of the research outcome on the CKD problem of Uddanam, Srikakulam is focused on testing the quality of ground water and establishing the cause for the disease [8–11]. There has been strong experimental evidence that concludes that the presence of high levels of heavy metals including cadmium in the ground water and the extensive use of pesticides is a general cause for the prevalence of CKD [12]. Other work includes detecting specific gene variants that cause a high risk of prevalence of CKD [13]. Despite the extensive research, the disease continues to plague the region. Although the research into the cause and effect of the CKD in Uddanam is extensive and exhaustive, there is less work on the relevant public health and policy measures. For example, several governmental health and welfare schemes have been proposed for CKD patients in Uddanam in the context of their socio-economic standards, including free dialysis, health awareness camps, free medication, etc. in [14, 15]. There have been propositions to include community engagement and public inclusion policy for effective tackling of the situation by the governments [16]. Based on the fact that research into the etiology of CKD is still underway, there is an increased need for more public policy initiatives to impede its effect on the residents [17]. The uncontrolled prevalence of the diseased called for development of sophisticated research cum health centres (hospitals) that co-jointly conduct research and also provide quality treatment to the patients. To this effect, the Government of Andhra Pradesh instituted the YSR Sujaladhara Uddanam Drinking Water Project [18] in collaboration with Megha Engineering to promote the use of purified minieral water over ground water. The water is supplied at subsidized prices and residents are strongly encouraged to stop drinking ground water.

Several research agencies and institutions have been involved in studying chronic kidney disease in Uddanam, Srikakulam. Some of these include (a) the Indian Council of Medical Research (ICMR) for conducting epidemiological studies and research projects to understand the prevalence, etiology, and risk factors associated with CKD,

(b) the National Institute of Nutrition (NIN) [19] for conducting research on the nutritional aspects and dietary factors related to CKD in Uddanam, (c) Achutha Menon Centre for Health Science Studies (AMCHSS) for studies focusing on the epidemiology and public health aspects of CKD in Uddanam, and (d) the Andhra University [20] for conducting collaborative studies on genetic predisposition and public policy. The prevalence of Uddanam was instrumental in evolving “hospitals” into “research hospitals”, research hospitals including the KIMS-ICON kidney research foundation, the Apollo hospitals, Government hospitals and diagnostic centers and the recently established Dr. YSR Kidney Research Centre and Super Specialty Hospital, Palasa, actively collaborate with local healthcare providers, government bodies, and international organizations to conduct multidisciplinary research and provide quality medical care to CKD patients [21]. The government has initiated several welfare schemes, in addition to the research medical facilities, including Arogyasri, free dialysis, free medication and monetary benefit of INR 10,000 (Rupees Ten Thousand) per month, to intersect the benefits of medical care and governmental assistance. A precise ambivalent analytic conclusion of the impact of the said initiatives in the past three years is not available to date. The next section presents the details of the survey.

3 Survey details

This section first presents the motivation for the survey and then the data preliminaries.

3.1 Motivation for the survey

The promulgation of research hospitals and welfare schemes in Uddanam in the current government's regime had positively impacted the lives of many CKD affected families in Uddanam. All hospitals and diagnostic centers have been upgraded with state-of- the-art facilities for dialysis. The Hon. Chief Minister of Andhra Pradesh recently opened the Dr. YSR Kidney Research Centre and Super Specialty Hospital, Palasa for specialized care of CKD patients. Moreover, the government also initiated a water supply plant, the YSR Sujaladhara Uddanam Drinking Water Project, in collaboration with Megha Engineering and Infrastructure Limited (MEIL) for a total budget of 700 crore rupees. The government topped the medical facilities with liberal welfare schemes in way of free dialysis and medication.

Defn. 3.1: Objective of the Government of Andhra Pradesh

In his inaugural speech of the opening of Dr. YSR Kidney Research Centre and Super Specialty Hospital, Hon. Chief Minister, Government of Andhra Pradesh said that the motto of the government is to ensure that no eligible soul in Uddanam should lose on the benefits of the government schemes.

In light of the sincere and serious efforts of the government in the past five years, a detailed statistical analysis of the positive, negative and missing aspects of govern- mental assistance in eradicating the prevalence of CKD and treating its victims is not available as a public article to date. This survey aims to fill the gap by statistically measuring the aforementioned objective of the Government of Andhra Pradesh and present the ambivalent impact of government schemes in terms of both medical and welfare assistance.

3.2 Survey preliminaries

The survey was conducted in 72 villages of the Srikakulam District, spanning several mandalas, namely, Palasa, Ichapuram, Kanchili, Sompeta, Kaviti, Mandasa and Vajrapu Kotturu, which have been seriously affected by the CKD. The data presented herein corresponds to our survey conducted over three months and culminated on 14-02-2024. During the survey, we have personally visited several medical facilities including the Government Hospital, Palasa, Dialysis Centre, Haripuram and the highly acclaimed Dr. YSR Kidney Research Centre and Super Specialty Hospital, Palasa recently inaugurated on 15-12-2023 by, Hon. Chief Minister, Government of Andhra Pradesh. The total number of CKD patients surveyed, i.e., the sample size, is 942, selected at absolute value[1] but randomly and uniformly from the aforementioned mandalas. Figure 1 shows the spatial distribution of the villages and medical centres visited to interview the CKD patients. The shown Uddanam region spans nearly 300 kilometers. The questionnaire and the raw statistical report are shown in Appendix A. In the sequel, we discuss the manifestation of CKD within the patients as a statistical characterization of their gender and the stage of the disease. We also discuss the statistical impact of the governmental schemes.

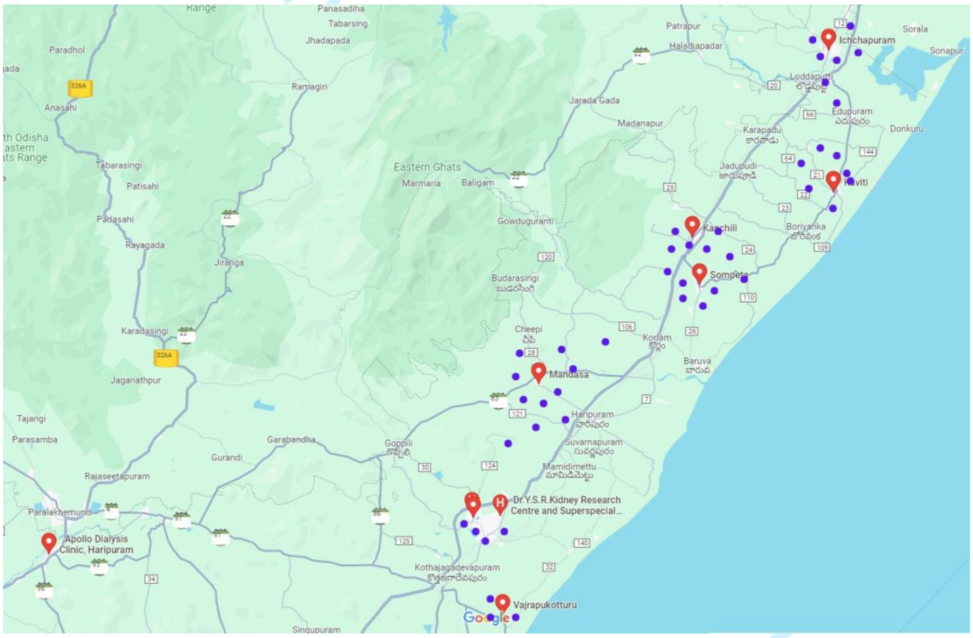


Fig. 1 The geographical distribution of the sample candidates surveyed, at random but uniformly from the aforementioned mandalas of Uddanam, Srikakulam.

[1]Absolute value means that all the 942 sample candidates are CKD patients.

4 The impact of government schemes

In this section, we present the key statistical features of the survey. Of the 942 individuals, 71% (669) are male and 29% (273) are female, shown in Figure 2. Nearly 81.8% of the total number of CKD patients surveyed are aged 45 years and more. Of the total sample size, 9.7% are in stage one, 35.15% in stage two, 41.21% in stage three, 2.42% in stage four and 11.52% in stage five. This is shown in Figure 3. The creatinine levels of CKD patients interviewed ranged from 0.9 to 10.0 which is indicative of the fact that a controlled value of the creatinine does not necessarily ensure perpetual

good health to the person. It has also been found that the progression of the severity of the CKD in both genders is synonymous with respect to both the sample size and the gender size. This trend can be observed in Figure 4. It can be observed that the proportion of people who advance to the final stages of the disease is higher in men than women. Women, on the other hand, who are a 1/3rd proportion of the total number of CKD infections, advance through stages one, two and three of the disease rapidly, but may not advance as much thereafter. This trend is in concurrence to the findings that the chances of the CKD advancing towards kidney failure are higher in men than women. A possible reason for this could be the presence of high testosterone and less estrogen [22].

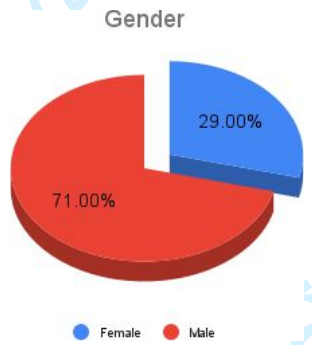


Fig. 2 The gender distribution of the total number of CKD patients interviewed.in Uddanam, Srikakulam.

Additionally, 67.8% of the people expressed their satisfaction about government reach to them through Asha workers, Village Volunteers and Gram Sachivalayam in aiding with respect to disease awareness and governmental assistance.

Based on the above findings, we infer that the number of people under 45 years of age who have been contracted with the CKD are only about 18% of the total sample size. This indicates that the number of CKD patients has seen a decreasing trend in the past three years as the Government of Andhra Pradesh has rigorously encouraged the use of purified mineral water over ground water. People are now being supplied with mineral water for a subsidized price of nearly INR 5.00 (Rupees Five Only) or less for 40 liters can. The YSR Sujaladhara Uddanam Drinking Water Project has been instrumental in supplying fresh mineral water round the year irrespective of the weather conditions to all the villages affected by CKD. While supplying mineral water has reduced the proportion of CKD detection in the past three years, the government welfare schemes such as free dialysis, free medication for CKD affected patients has prolonged their lives. There are people who undergo free dialysis nearly thrice every week with a hope they shall live another day.

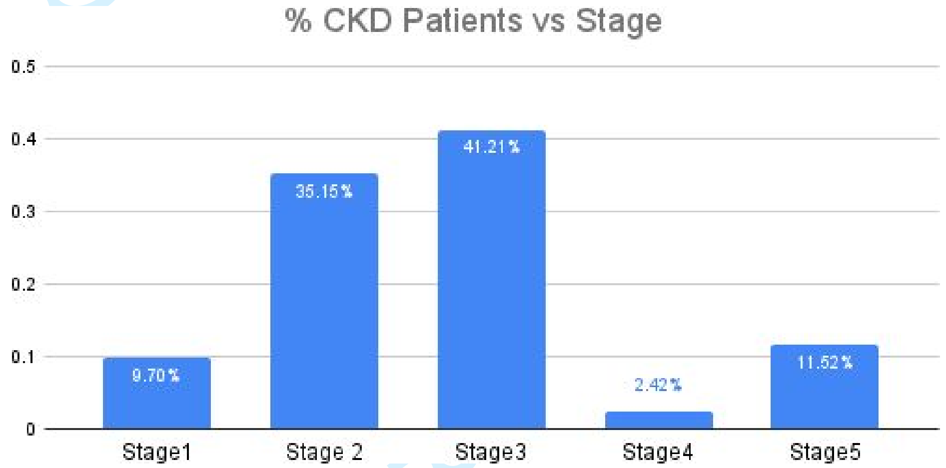


Fig. 3 The stage-wise distribution of the total number of CKD patients.

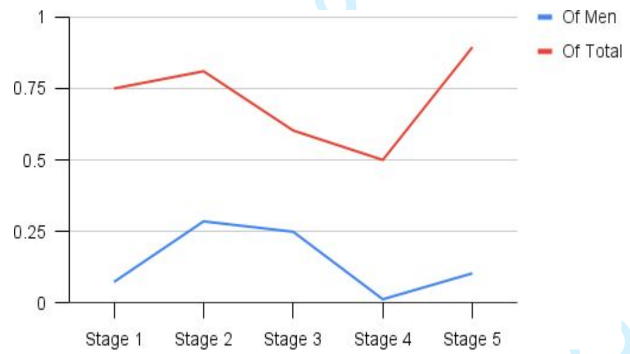
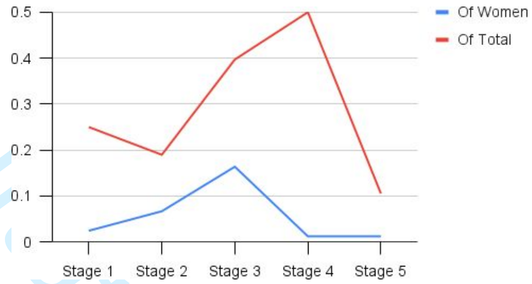


Fig. 4 The top panel shows the ratio of men affected with CKD with respect to the total sample size (red) and the total number of men (blue) as a function of the stage of the disease. The bottom panel shows the ratio of the women affected with CKD with respect to the total sample size (red) and the total number of women (blue) as a function of the stage of the disease.

4.1 Challenges

Despite the tremendous contribution of the government in providing medical care to current patients, there are certain aspects brought to light from our research survey that could create an impact in saving more lives than now. In this section, we present the data for the same. From our research survey, it has been surprisingly found that of the total sample size of 942 interviewed CKD patients, only 13.27% (125 Nos.) have recorded that they have



benefited directly from government welfare schemes while the remaining 86.73% (817 Nos.) recorded in the negative, as shown in Figure 5.

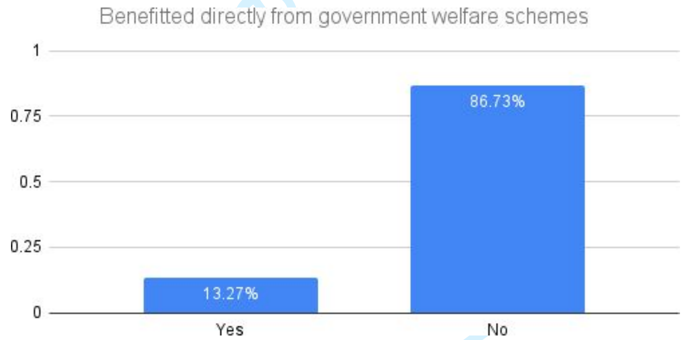


Fig. 5 The % of CKD patients who voted in positive and in negative for receiving benefit from the government as welfare schemes.

Of the 125 people who have benefited, 13.6% belong to stage four and the remain- ing 86.4% to stage five. There are no patients in stages one, two and three who have answered in the positive for having benefited from the government schemes. Of the 817 people who reportedly have not benefited, 11.18% belong to stage one, 40.55% to stage two, 47.55% to stage three and 0.06% to stage four. There are no patients in stage five. The said data is shown in Figure 6.

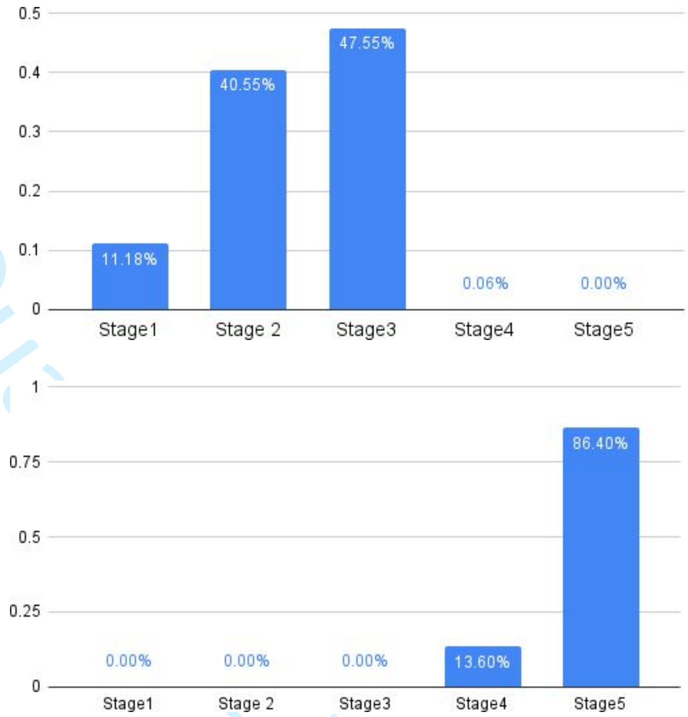


Fig. 6 The top panel shows the % of CKD patients who did not receive any government benefit versus the stage of the disease. The bottom panel shows the % of CKD patients who received any government benefit versus the stage of the disease.

This data has caused much surprise, to the extent that we did a second level survey by interviewing candidates randomly from among the both categories, which seconded the findings. As a concurrence for the above findings, when asked how the government could assist the CKD patients, 51.75% requested for advanced medication in early stages, 45.61% requested for more CKD awareness programs and the remain- ing requested for financial assistance for long travel. Moreover, almost all patients suggested that the medicines prescribed by the doctors are unavailable in the list of medicines provided for free by the government, and they are burdened by around INR 5,000 (Rupees Five Thousand) to INR 10,000 (Rupees Ten Thousand). This infers that CKD patients in stages four and five are the ones benefiting from government welfare schemes while those in stages one, two and three are reportedly not benefiting to their satisfaction from government schemes. As an indication of more concurrence to the finding, only 14.85% indicated that they have been personally benefited from government schemes, meaning that nearly 84% of the people, especially those belonging to stages one, two and three, have not received any perceivable government assistance. Moreover, as mentioned in section 4, nearly 67% of the people have received support directly through government health support staff, it is indeed a surprise that only 11% of the total candidates interviewed are benefiting from the use of digital technology for purposes including remote consultation, online verification of medical records, online reception of medical test results, online payments, etc.

It has been found that the people are used to receiving help in terms of governmental schemes, awareness, etc. through only governmental health workers who themselves are incapacitated to travel long distances and reach out stage 4 patients who should be isolated. The penetration of technology to rural population as this requires a deeper and stronger push from government and non-government agencies. This is in line with our discovery that only 2.27% of the people interviewed have good access to technology. The route to achieve higher digital penetration is through more physical awareness camps that reach the doorsteps of the people. When the final stage patients have been asked what best can be done at that stage, we have observed that most of them have made peace with themselves (which was an emotional ordeal for us) and 11\% of them requested for financial assistance to their spouses or children and most of them for financial aid to early-stage patients.

5 Key inferences and proposed policies

Based on the above findings, it could be inferred that the patients suffering from CKD stage three and four, for whom the creatinine levels would be in the range 5.0 to 10.0 and for whom the chances for survival are minuscule, are being provided the expensive dialysis cum medication treatment for free by the government. While this is commendable, the proportion of people benefited from this is only 13.94% of the total sample size. This perfectly corroborates that only 13.3% reported of having benefited directly from government welfare schemes. It is also the case that most of the people who benefit from free dialysis in their advanced stages of CKD eventually succumb to the disease. On the other hand, a large proportion of people, i.e., nearly 86.06% suffering from stage one, two and three of the CKD but not requiring any dialysis, are not benefiting in a major sense. This perfectly corroborates that a whopping 89.6% reported of having not benefited directly from government welfare schemes. That is to say, there is a great scope for the government to provide advanced medical facility for free to CKD patients in their early stages to increase their chances of survival. The key inferences of this paper are outlined as follows,

- The increased use of mineral water over ground water has caused a decreased record of the number of CKD cases in the past three years.

- The government reach to CKD patients through health workers and Sachivalayam have found much reach to the patients with respect to creating awareness about government welfare schemes.
- The free dialysis provided by the government to advanced stage CKD patients has been a boon by increasing their lifespan.
- The government welfare schemes are majorly benefiting patients who are in advanced stages of the disease. Despite the expensive dialysis and medication pro- vided for free by the government, these patients, in most cases, eventually succumb to the disease.
- There is an immediate need for government intervention and allocation of fund for welfare schemes for patients in their early stage of CKD so their progression towards advanced stage is decelerated, or prohibited.

Our research, as summarized above, has identified the positive impact and hope instilled by the Government of Andhra Pradesh in (a) deterring the prevalence of the disease by providing mineral water, and (b) providing advanced medical treatment to patients in advanced stages of the disease. As a first, this paper identifies the void in providing advanced medical care to patients in early stages of CKD as a statistical measure of their age, gender and stage of the disease. Therefore, there is an immediate need for providing advanced medical care to patients in early stages of their disease. From the survey, we observe the following, (a) it is critical to start advanced medication to patients in their early stages of the disease in order to impede the progression towards advanced stages, (b) it is also critical to ensure that the advanced medication prescribed by the doctors is available within the free medication list, (c) most importantly, the government should regulate the prescriptions of doctors to within the free medicines list and ensure private parties are not profited as the expense of a poor man's disease, (d) the number of super specialty hospitals is few for the wide range of Uddanam region and so the government should focus on providing free transport to patients or increasing the number of medical health outlets, (e) it is undoubtedly a surprise that fruit of digital technology has not reached the far corners of Uddanam, hence the government should take measures to increase the promulgation of the use of smart mobile phones by the patients for medical issues, and (f) the government should regularly organise awareness camps on the severity of the disease so even the slightest symptom of CKD will not go unnoticed. To summarise, this paper suggests the following public policy measures to be initiated by the government to overcome the challenges identified hitherto,

- Provide free medication and diagnostic facilities for continuous monitoring of creatinine for early-stage patients.
- Provide fully free public and private transport to CKD patients to visit the hospital regularly.

- Conduct regular awareness camps at the village level for patients and their families to understand the implications of CKD and the available governmental assistance.
- To promulgate the use of technology by giving free smartphones for receiving medical reports, consulting the doctor using web apps, etc.

6 Conclusion

This paper is the first to statistically measure the impact of medical and welfare schemes of the Government of Andhra Pradesh in prohibiting the prevalence of CKD in Uddanam villages and the treatment provided to its patients in the past three years. This paper primarily identified that the majority of the current government schemes are targeted towards free dialysis to patients who are in advanced stages of the disease while a minor proportion is allocated to those in their early stages. Public policy and health measures to address the problem are herein proposed in concurrence with the opportunities and challenges of the region. Additionally, this paper presented the reach of both the government and technology in reaching the people directly for medical benefit.

Declarations

- Funding: Not applicable.

- Conflict of interest/Competing interests (check journal-specific guidelines for which heading to use): The authors declare no conflict of interest.
- Ethics approval and consent to participate: Not applicable.
- Consent for publication: Not applicable.
- Data availability: Survey data is made available in raw format in Appendix A.
- Materials availability: Not applicable.
- Code availability: Not applicable.
- Author contribution

Appendix A Survey report

Personal Details

1. Gender
   - Male — 71%
   - Female — 29%
2. Age
   - < 18 years — 0.61%
   - 18-30 years — 3.64%
   - 31-45 years — 13.94%
   - 46-60 years — 47.88%
   - > 60 years — 33.94%
3. Occupation
   - Farmer — 40.13%
   - Agricultural laborer — 32.24%
   - Non-agricultural laborer — 23.68%
   - Others — 3.95%
4. Education level
   - No formal education — 49.70%
   - Primary school — 40.06%
   - Secondary school — 7.82%
   - College/University — 2.42%

Health Profile

1. Do you have any known kidney-related health issues?
   - Yes — 100%
   - No — 0%
2. Have you been diagnosed with chronic kidney disease (CKD)?
   - Yes — 100%
   - No — 0%
3. If yes, what stage of CKD have you been diagnosed with?

- Stage 1 — 9.7%
- Stage 2 — 35.15%
- Stage 3 — 41.21%
- Stage 4 — 2.42%
- Stage 5 — 11.52%

4. Do you have a family history of kidney disease?

- Yes — 3.13%
- No — 96.88%

5. What are the early symptoms of your disease?

- Swelling in your hands or feet — 55.56%
- Urinary Tract infections — 32.10%
- Blood in urine — 0.61%
- Kidney damage shown in scans — 11.73%

Lifestyle and habits

1. Do you consume well water for drinking purposes?

- Yes — 14.2%
- No — 85.8%

2. How many liters of water do you consume per day on average?

- < 1 — 49.08%
- 1-2 — 41.11%
- 2-3 — 7.36%
- > 3 — 2.45%

3. Do you consume alcohol?

- Yes — 93.94%
- No — 6.06%

4. Do you smoke tobacco or use any other forms of tobacco?

- Yes — 93.33%
- No — 6.67%

5. How often do you exercise per week?

- None — 83.64% (but they all work hard)

- 1-2 times — 16.4%
- 3-4 times — 0%
- 5 or more times — 0%

6. How often do you consume processed or fast food per week?

- Never — 29.7%
- Rarely — 62.42%
- Occasionally — 7.27%
- Frequently — 0.61%

Treatment, health care and awareness

1. Are you aware of chronic kidney disease and its symptoms?

- Yes — 64.42%
- No — 35.58%

2. Are you aware of any government health initiatives specifically aimed at addressing chronic kidney disease in your region, especially the Uddanam Kidney Hospital and Research Center?

- Yes — 62.96%
- No — 37.08%

3. If yes, please specify the initiatives you are aware of:

- Free dialysis — 91.18%
- Free medication — 2.50%
- INR 10,000 monetary benefit — 0.44%
- Government health worker support — 5.88%

4. How would you rate the effectiveness of government health programs in addressing CKD in your community?

- Very effective — 24.6%
- Not effective at all — 76.4%

5. Have you personally benefited from any government-sponsored healthcare services or programs related to CKD?

- Yes — 13.27%
- No — 86.73%

6. In your opinion, what further steps or measures should the state government take to address the issue of CKD effectively in your community?
   - Free medication — 51.75%
   - Awareness programs — 45.61%
   - Travel assistance — 2.64%
7. Have you received any awareness or information on preventing kidney disease from government healthcare professionals?
   - Yes — 54.09%
   - No — 45.91%

Financial impact

1. How would you describe the financial impact of managing CKD on your household in Uddanam?
   - Significant burden — 84.57%
   - Moderate burden — 6.17%
   - Minor burden — 9.26%
2. Which of the following expenses related to CKD have you or your family incurred in the past year in the Uddanam region?
   - Medications — 90.06%
   - Dialysis — 3.11%
   - Transportation to hospital — 6.83%
3. On average, how much do you spend on managing your CKD related expenses?
   - Less than INR 5,000 — 4.26%
   - 5,000 – 10,000 INR — 6.71%
   - 10,000 – 20,000 INR — 82.32%
   - More than 20,000 INR — 6.70%
4. Are you aware of any government subsidies or benefits available specifically for people affected by CKD in Uddanam?
   - Yes — 67.88%
   - No — 32.12%
5. If yes, which government subsidies are you aware of?
   - Financial Assistance to medical treatment — 4.2%

- Free dialysis — 95.80%
- Others — 0%

6. Have you or any of your family members benefited from any government subsidies related to CKD in Uddanam?
    - Yes — 85.98%
    - No — 14.02%
7. How would you rate the effectiveness of the state government in proactively treating the CKD affected people and helping manage related expenses?
    - Excellent — 0.61%
    - Good — 20.12%
    - Somewhat good — 58.54%
    - Poor — 20.73%

Technology

1. Do you use smartphone technology for matters related to CKD treatment including payment, health trackers, online medical reports, remote doctor consultation?
    - Yes — 6.67%
    - No — 93.33%
2. Do you support the use of recent technology in diagnosis and prognosis of CKD?
    - Yes — 45.15%
    - No — 54.85%
3. Have you been provided adequate training in use of technology for your medical needs?
    - Yes - 2.27%
    - No - 60.28%
    - Health worker does the job - 37.45%
4. Have you attended awareness camps on CKD?
    - Yes - 10.21%
    - No - 89.79%
5. What do you appreciate about the recent governmental attempts to provide superior medical care?
    - More medical health centers - 85.71%
    - Awareness camps - 12.21%
    - Technology penetration - 2.08%
6. What is the best help government can provide you, at this stage in your life?

- Financial support to family members after I pass away - 10.92%
- Financial support to early-stage patients - 60.95%
- More medical centers and easy access facilities - 28.13%

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Response to Review Comments of

The ambivalent impact of government schemes on chronic kidney disease patients in Uddanam, India: A qualitative study

Chief Editor

Comment: The reviewer(s) have recommended publication, subject to minor revisions to your manuscript. Therefore, I invite you to respond to the reviewer(s)' comments and revise your manuscript in accordance with their suggestions, or provide a rationale for not accepting their recommendations.

Response: We thank the chief editor, the editorial team and the anonymous reviewers for their constructive comments. We have improved the paper on each point as outlined below

Reviewer 1:

Comment: I appreciate your efforts in identifying a chronic problem and elaborating on the effective measures. However, the sample size is limited within the given scope to draw conclusions. The survey could have incorporated broader view of questions entailing the analysis of needs for CKD patients.

The paper can be accepted for publication. Yes, relevant literature has been reviewed with regard to the problem identified and adequate sources were mentioned to justify the importance of the condition in that area. The results are presented clearly and analysed appropriately. The conclusions are adequate. The paper identifies key implications pertaining to the existing problem and highlights the need for further research. The implications are consistent with the findings and conclusions of the paper.

Response: We thank the reviewer for the comments.

Comment: The methodology seems to be explicit and the paper is well designed. The methods employed are appropriate but the survey could have included some more questions. The questions included in the survey are limited and does not encompass a broader spectrum of identified problem

Response: We have conducted a quick survey through phone calls and have included four new questions on the aspects of the use of technology and its role and the government's role in creating awareness on treatment and prevention of the CKD. They are included in Appendix A. Also a brief analysis of the questions are included in section 4.

Comment: The language is not very lucid and structuring of words seems to be incomplete as hyphen(-) is used in words like factors, metals, governmental which is not required. Certain instances where hyphen is required like socio-economic, multi-factorial were ignored.

Response: We thank the reviewer for pointing this out. We have corrected these errors now.

The ambivalent impact of government schemes on chronic kidney disease patients in Uddanam, India: A qualitative study

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Abstract

Uddanam, Srikakulam in Andhra Pradesh, a conglomeration of an apportioned group of villages, grapples with a severe and mysterious kidney disease epidemic since the 1980s, affecting agricultural communities. The region, which was once fondly called "Udyanam," translated as "Garden," for its richness in greenery and cashew and coconut trees, has now become "Uddanam," the land of death and despair. The residents of the region suffer with high rates of kidney failure and associated health complications for factors including environmental toxins and poor water quality. Despite several efforts by governments, the impact of governmental policy on improving the conditions has been non-significant. The problem has been taken into sincere and serious consideration by the present Government of Andhra Pradesh which introduced ground-breaking welfare initiatives to impede the prevalence of the disease and the deaths among patients. This paper presents a analytic report, with precise scientific rigor, the positive impact of the government's welfare schemes, and the areas that need urgent public policy intervention. This paper is the first to identify, that out of the total of

942 CKD patients interviewed uniformly at random from the Uddanam mandals, a majority of 86.06%, who belong to advanced stages, receive advanced governmental (free) medical care, and soon succumb to the disease, and a minority of 13.94%. who belong to early stages of the disease, do not benefit directly from government welfare schemes, and hence perpetually proceed to advanced stages. This paper also proposes health and public policy measures to overcome this challenge.

Keywords: Chronic kidney disease, Uddanam, government welfare schemes, free dialysis, public health policy, society

1 Introduction

The Uddanam region in the Srikakulam district of Andhra Pradesh, India, has gained significant attention in recent years due to the high prevalence of chronic kidney disease (CKD) among its residents. The region has been identified as one of the global hot spots for CKD of unknown origin (CKDu), characterized by its disproportionate impact on agricultural communities. The multi factorial etiology of CKD in Uddanam, including environmental, occupational, and socioeconomic factors, presents complex challenges for disease management and prevention. Understanding the epidemiology and risk factors associated with CKD in Uddanam is crucial for designing targeted interventions and healthcare policies to mitigate its impact on affected communities. Furthermore, investigating the genetic, environmental, and lifestyle factors contributing to the high prevalence of CKD in Uddanam can provide valuable insights into the broader implications of kidney disease on a global scale. Efforts to address the CKD epidemic in Uddanam require a multidisciplinary approach, involving collaboration between healthcare professionals, researchers, policymakers, and community stakeholders. By elucidating the significance of Uddanam Srikakulam in the context of CKD research, this paper underscores the ambivalent impact of the Andhra Pradesh Government schemes in mitigating its prevalence in the region and the public health interventions and research initiatives aimed at addressing the underlying determinants of kidney disease in affected populations.

The rest of the paper is organised as follows. Section 2 presents the historical perspective of CKD, its prevalence in Uddanam villages, relevant research, and the government initiatives to counter the same. Section 3 sets the motivation for the survey and discusses the preliminaries and the methods thereof. Section 4 presents the ambivalent impact of the current government schemes on the CKD patients of Uddanam. This is followed by the proposal of public policy measures to counter the identified snags in section 5 and the concluding remarks in section 6.

2 Historical perspective and related work

The historical aspect of the CKD in Uddanam, Srikakulam, dates back several decades, with reports of kidney related health issues emerging as early as the 1980s [1, 2]. However, the prevalence of CKD gained significant attention in the early 2000s when it was recognized as a widespread health crisis affecting a large portion of the population, particularly in the agricultural communities of Uddanam. The condition was characterized by a high incidence of kidney failure and related complications among residents [3], leading to a substantial burden on healthcare resources and significant socioeconomic impacts on affected families. The historical aspect of CKD in Uddanam is marked by the gradual recognition of its scale and severity over time. Several factors have been proposed as potential contributors to the development of CKD in Uddanam, including environmental toxins, poor water quality, agricultural chemicals, and socioeconomic factors such as poverty and lack of access to healthcare [4]. The historical context of CKD in Uddanam underscores the complexity of the disease and the challenges associated with identifying its underlying causes. Over the years, various governmental and non-governmental organisations have initiated efforts to address the CKD crisis in Uddanam [5]. The first fruits of these initiatives along with the most rigorous government schemes proposed in the past three years are now bearing in the leadership of Shri Y.S. Jagan Mohan Reddy, Hon. Chief Minister, Government of Andhra Pradesh, for initiatives including health screening programs, research studies, infrastructure development, subsidies, and public awareness campaigns. This paper aims to bring to light the two-sided impact of these initiatives in the past three years.

The Uddanam, Srikakulam is so plagued by the disease that nearly 30% of the total population suffers from the disease [6, 7]. The majority of the research outcome on the CKD problem of Uddanam, Srikakulam is focused on testing the quality of ground water and establishing the cause for the disease [8–11]. There have been strong experimental evidence that concludes that the presence of high levels of heavy metals including cadmium in the ground water and the extensive use of pesticides is a general cause for the prevalence of CKD [12]. Other work include detecting specific gene variants that cause a high risk of prevalence of CKD [13]. Despite the extensive research, the disease continues to plague the region. Although the research into the cause and effect of the CKD in Uddanam is extensive and exhaustive, there is less work on the relevant public health and policy measures. For example, several governmental health and welfare schemes have been proposed for CKD patients in Uddanam in the context of their socio-economic standards, including free dialysis, health awareness camps, free medication, etc. in [14, 15]. There have been propositions to include community engagement and public inclusion policy for effective tackling of the situation by the governments [16]. Based on the fact that research into the etiology of CKD is still underway, there is an increased need for more public policy initiatives to impede its effect on the residents [17]. The uncontrolled prevalence of the diseased called for development of sophisticated research cum health centres (hospitals) that co-jointly conduct research and also provide quality treatment to the patients. To this effect, the Government of Andhra Pradesh instituted the YSR Sujaladhara Uddanam Drinking Water Project [18] in collaboration with Megha Engineering to promote the use of purified minieral water over ground water. The water is supplied at subsidised prices and residents are strongly encouraged to stop drinking ground water.

Several research agencies and institutions have been involved in studying Chronic Kidney Disease in Uddanam, Srikakulam. Some of these include (a) the Indian Council of Medical Research (ICMR) for conducting epidemiological studies and research projects to understand the prevalence, etiology, and risk factors associated with CKD, (b) the National Institute of Nutrition (NIN) [19] for conducting research on the nutritional aspects and dietary factors related to CKD in Uddanam, (c) Achutha Menon

Centre for Health Science Studies (AMCHSS) for studies focusing on the epidemiology and public health aspects of CKD in Uddanam, and (d) the Andhra University [20] for conducting collaborative studies on genetic predisposition and public policy. The prevalence of Uddanam was instrumental in evolving "hospitals" into "research hospitals", research hospitals including the KIMS-ICON kidney research foundation, the Apollo hospitals, Government hospitals and diagnostic centers and the recently established Dr. YSR Kidney Research Centre and Super Specialty Hospital, Palasa, actively collaborate with local healthcare providers, government bodies, and international organizations to conduct multidisciplinary research and provide quality medical care to CKD patients [21]. The government has initiated several welfare schemes, in addition to the research medical facilities, including Arogyasri, free dialysis, free medication and monetary benefit of INR 10,000 (Rupees Ten Thousand) per month, to intersect the benefits of medical care and governmental assistance. A precise ambivalent analytic conclusion of the impact of the said initiatives in the past three years is not available to date. The next section presents the details of the survey.

3 Survey details

This section first presents the motivation for the survey and then the data preliminaries.

3.1 Motivation for the survey

The promulgation of research hospitals and welfare schemes in Uddanam in the current government's regime had positively impacted the lives of many CKD affected families in Uddanam. All hospitals and diagnostic centers have been upgraded with state-of-the-art facilities for dialysis. The Hon. Chief Minister of Andhra Paadesh recently opened the Dr. YSR Kidney Research Centre and Super Specialty Hospital, Palasa for specialised care of CKD patients. Moreover, the government also initiated a water supply plant, the YSR Sujaladhara Uddanam Drinking Water Project, in collaboration with Megha Engineering and Infrastructure Limited (MEIL) for a total budget of

700 crore rupees. The government topped the medical facilities with liberal welfare schemes in way of free dialysis and medication.

Defn. 3.1: Objective of the Government of Andhra Pradesh

In his inaugural speech of the opening of Dr. YSR Kidney Research Centre and Super Specialty Hospital, Shri Y.S. Jagan Mohan Reddy, Hon. Chief Minister, Government of Andhra Pradesh said that the motto of the government is to ensure that no eligible soul in Uddanam should lose on the benefits of the government schemes.

In light of the sincere and serious efforts of the government in the past five years, a detailed statistical analysis of the positive, negative and missing aspects of governmental assistance in eradicating the prevalence of CKD and treating its victims is not available as a public article to date. This survey aims to fill the gap by statistically measuring the aforementioned objective of the Government of Andhra Pradesh and present the ambivalent impact of government schemes in terms of both medical and welfare assistance.

3.2 Survey preliminaries

The survey was conducted in 72 villages of the Srikakulam District, spanning several mandals, namely, Palasa, Ichapuram, Kanchili, Sompeta, Kaviti, Mandasa and Vajrapu Kotturu, which have been seriously affected by the CKD. The data presented herein corresponds to our survey conducted over three months and culminated on 14-02-2024. During the survey, we have personally visited several medical facilities including the Government Hospital, Palasa, Dialysis Centre, Haripuram and the highly acclaimed Dr. YSR Kidney Research Centre and Super Specialty Hospital, Palasa recently inaugurated on 15-12-2023 by Shri Y. S. Jagan Mohan Reddy, Hon. Chief Minister, Government of Andhra Pradesh. The total number of CKD patients surveyed, i.e., the sample size, is 942, selected at absolute value[1] but randomly and uniformly from the aforementioned mandals. Figure 1 shows the spatial distribution

[1]Absolute value means that all the 942 sample candidates are CKD patients.

of the villages and medical centres visited to interview the CKD patients. The shown Uddanam region spans nearly 300 kilometers. The questionnaire and the raw statistical report are shown in Appendix ??. In the sequel, we discuss the manifestation of CKD within the patients as a statistical characterisation of their gender and the stage of the disease. We also discuss the statistical impact of the governmental schemes.

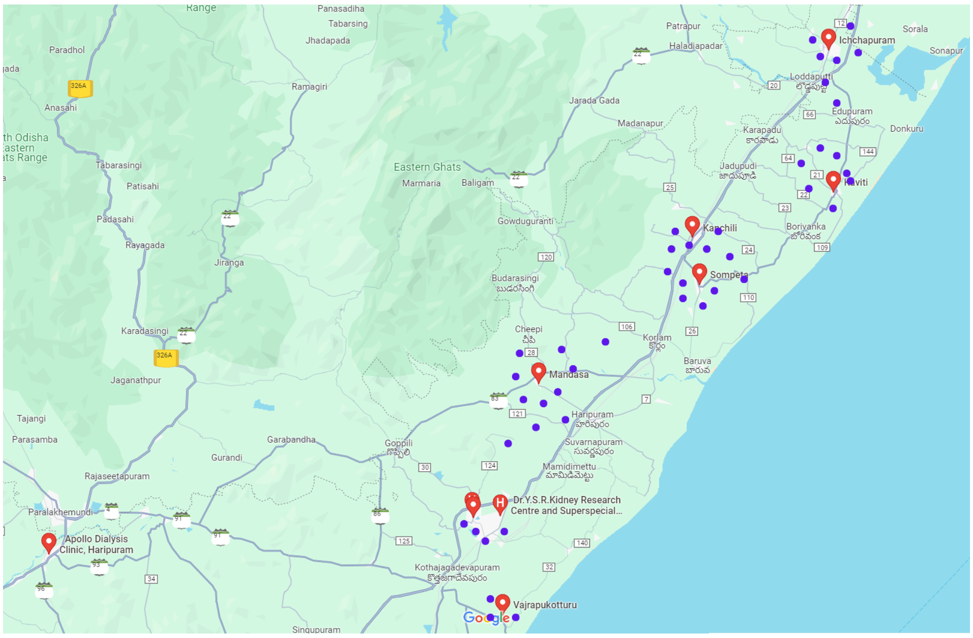

Fig. 1 The geographical distribution of the sample candidates surveyed, at random but uniformly from the aforementioned mandals of Uddanam, Srikakulam.

4 The impact of government schemes

In this section, we present the key statistical features of the survey. Of the 942 individuals, 71% (669) are male and 29% (273) are female, shown in Figure 2. Nearly 81.8% of the total number of CKD patients surveyed are aged 45 years and more. Of the total sample size, 9.7% are in stage one, 35.15% in stage two, 41.21% in stage three, 2.42% in stage four and 11.52% in stage five. This is shown in Figure 3. The creatinine levels of CKD patients interviewed ranged from 0.9 to 10.0 which is indicative of the fact that a controlled value of the creatinine does not necessarily ensure perpetual

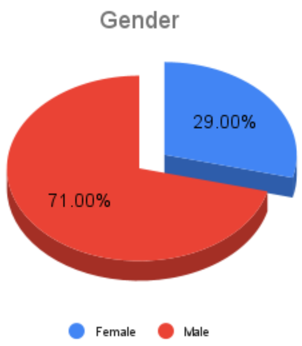

Fig. 2 The gender distribution of the total number of CKD patients interviewed.in Uddanam, Srikakulam.

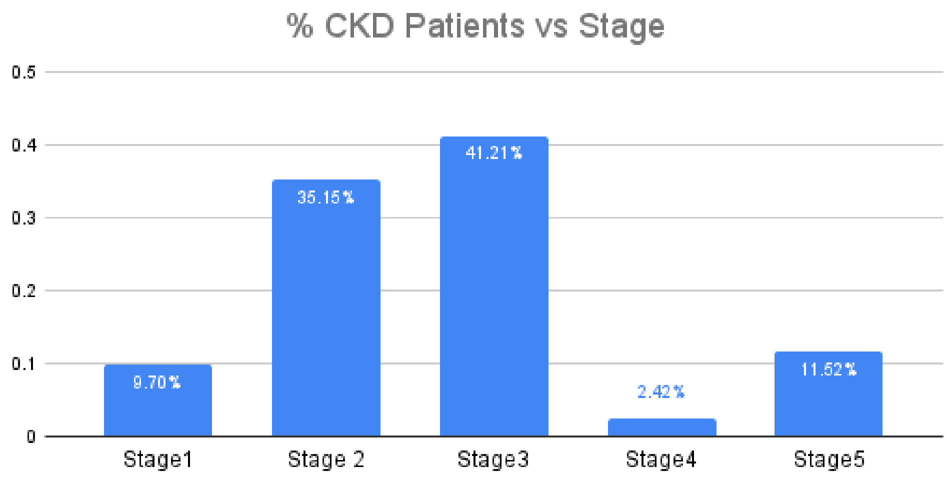

Fig. 3 The stage-wise distribution of the total number of CKD patients.

good health to the person. It has also been found that the progression of the severity of the CKD in both genders is synonymous with respect to both the sample size and the gender size. This trend can be observed in Figure 4. It can be observed that the proportion of people who advance to the final stages of the disease is higher in men than women. Women, on the other hand, who are a 1/3rd proportion of the total number of CKD infections, advance through stages one, two and three of the disease rapidly, but may not advance as much thereafter. This trend is in concurrence to the findings that the chances of the CKD advancing towards kidney failure are higher in men than women. A possible reason for this could be the presence of high testosterone and less estrogen [22].

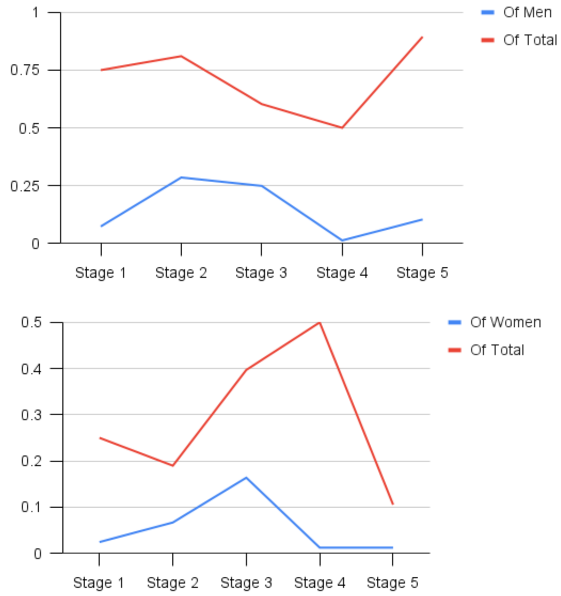

Fig. 4 The top panel shows the ratio of men affected with CKD with respect to the total sample size (red) and the total number of men (blue) as a function of the stage of the disease. The bottom panel shows the ratio of the women affected with CKD with respect to the total sample size (red) and the total number of women (blue) as a function of the stage of the disease.

Additionally, 67.8% of the people expressed their satisfaction about government reach to them through Asha workers, Village Volunteers and Gram Sachivalayam in aiding with respect to disease awareness and governmental assistance.

Based on the above findings, we infer that the number of people under 45 years of age who have been contracted with the CKD are only about 18% of the total sample size. This indicates that the number of CKD patients has seen a decreasing trend in the past three years as the Government of Andhra Pradesh has rigorously encouraged the use of purified mineral water over ground water. People are now being supplied with mineral water for a subsidized price of nearly INR 5.00 (Rupees Five Only) or less for a 40 liters can. The YSR Sujaladhara Uddanam Drinking Water Project has been instrumental in supplying fresh mineral water round the year irrespective of the weather conditions to all the villages affected by CKD. While supplying mineral water has reduced the proportion of CKD detection in the past three years, the government welfare schemes such as free dialysis, free medication for CKD affected patients has prolonged their lives. There are people who undergo free dialysis nearly thrice every week with a hope they shall live another day.

4.1 Challenges

Despite the tremendous contribution of the government in providing medical care to current patients, there are certain aspects brought to light from our research survey that could create an impact in saving more lives than now. In this section, we present the data for the same. From our research survey, it has been surprisingly found that of the total sample size of 942 interviewed CKD patients, only 13.27% (125 Nos.) have recorded that they have benefited directly from government welfare schemes while the remaining 86.73% (817 Nos.) recorded in the negative, as shown in Figure 5.

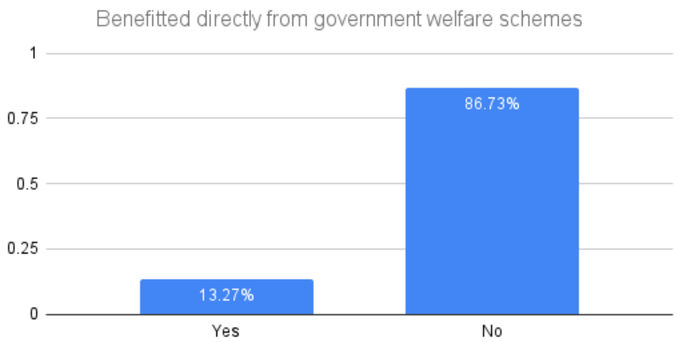

Fig. 5 The % of CKD patients who voted in positive and in negative for receiving benefit from the government as welfare schemes.

Of the 125 people who have benefited, 13.6% belong to stage four and the remaining 86.4% to stage five. There are no patients in stages one, two and three who have answered in the positive for having benefited from the government schemes. Of the 817 people who reportedly have not benefited, 11.18% belong to stage one, 40.55% to stage two, 47.55% to stage three and 0.06% to stage four. There are no patients in stage five. The said data is shown in Figure 6.

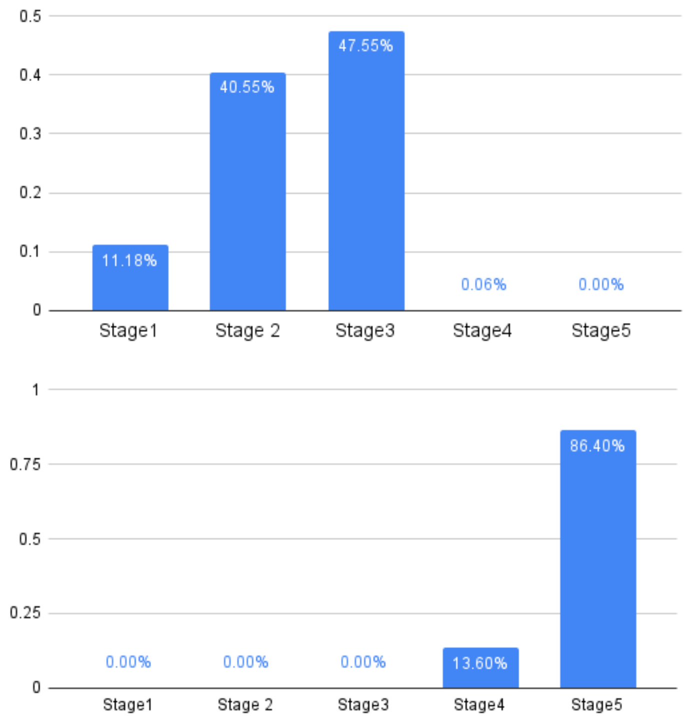

Fig. 6 The top panel shows the % of CKD patients who did not receive any government benefit versus the stage of the disease. The bottom panel shows the % of CKD patients who received any government benefit versus the stage of the disease.

This data has caused much surprise, to the extent that we did a second level survey by interviewing candidates randomly from among the both categories, which seconded the findings. As a concurrence for the above findings, when asked how the government could assist the CKD patients, 51.75% requested for advanced medication in early stages, 45.61% requested for more CKD awareness programs and the remaining requested for financial assistance for long travel. Moreover, almost all patients suggested that the medicines prescribed by the doctors are unavailable in the list of medicines provided for free by the government, and they are burdened by around INR 5,000 (Rupees Five Thousand) to INR 10,000 (Rupees Ten Thousand). This infers that CKD patients in stages four and five are the ones benefiting from government welfare schemes while those in stages one, two and three are reportedly not benefiting to their satisfaction from government schemes. As an indication of more concurrence to the finding, only 14.85% indicated that they have been personally benefited from government schemes, meaning that nearly 84% of the people, especially those belonging to stages one, two and three, have not received any perceivable government assistance. Moreover, as mentioned in section 4, nearly 67% of the people have received support directly through government health support staff, it is indeed a surprise that only 11% of the total candidates interviewed are benefiting from the use of digital technology for purposes including remote consultation, online verification of medical records, online reception of medical test results, online payments, etc.

5 Key inferences and proposed policies

Based on the above findings, it could be inferred that the patients suffering from CKD stage three and four, for whom the creatinine levels would be in the range 5.0 to 10.0 and for whom the chances for survival are minuscule, are being provided the expensive dialysis cum medication treatment for free by the government. While this is commendable, the proportion of people benefited from this is only 13.94% of the total sample size. This perfectly corroborates that only 13.3% reported of having benefited directly from government welfare schemes. It is also the case that most of the people who benefit from free dialysis in their advanced stages of CKD eventually succumb to the disease. On the other hand, a large proportion of people, i.e., nearly 86.06% suffering from stage one, two and three of the CKD but not requiring any dialysis, are not benefiting in a major sense. This perfectly corroborates that a whopping 89.6% reported of having not benefited directly from government welfare schemes. That is to say, there is a great scope for the government to provide advanced medical facility for free to CKD patients in their early stages to increase their chances of survival. The key inferences of this paper are outlined as follows,

- The increased use of mineral water over ground water has caused a decreased record of the number of CKD cases in the past three years.

- The government reach to CKD patients through health workers and Sachivalayam have found much reach to the patients with respect to creating awareness about government welfare schemes.
- The free dialysis provided by the government to advanced stage CKD patients has been a boon by increasing their lifespan.
- The government welfare schemes are majorly benefiting patients who are in advanced stages of the disease. Despite the expensive dialysis and medication provided for free by the government, these patients, in most cases, eventually succumb to the disease.
- There is an immediate need for government intervention and allocation of fund for welfare schemes for patients in their early stage of CKD so their progression towards advanced stage is decelerated, or prohibited.

Our research, as summarized above, has identified the positive impact and hope instilled by the Government of Andhra Pradesh in (a) deterring the prevalence of the disease by providing mineral water, and (b) providing advanced medical treatment to patients in advanced stages of the disease. As a first, this paper identifies the void in providing advanced medical care to patients in early stages of CKD as a statistical measure of their age, gender and stage of the disease. Therefore, there is an immediate need for providing advanced medical care to patients in early stages of their disease. From the survey, we observe the following, (a) it is critical to start advanced medication to patients in their early stages of the disease in order to impede the progression towards advanced stages, (b) it is also critical to ensure that the advanced medication prescribed by the doctors is available within the free medication list, (c) most importantly, the government should regulate the prescriptions of doctors to within the free medicines list and ensure private parties are not profited as the expense of a poor man's disease, (d) the number of super speciality hospitals is few for the wide range of Uddanam region and so the government should focus on providing free transport to patients or increasing the number of medical health outlets, (e) it is undoubtedly a surprise that fruit of digital technology has not reached the far corners of Uddanam, hence the government should take measures to increase the promulgation of the use of smart mobile phones by the patients for medical issues, and (f) the government should regularly organise awareness camps on the severity of the disease so even the slightest symptom of CKD will not go unnoticed. To summarise, this paper suggests the following public policy measures to be initiated by the government to overcome the challenges identified hitherto,

- Provide free medication and diagnostic facilities for continuous monitoring of creatinine for early stage patients.
- Provide fully free public and private transport to CKD patients to visit the hospital regularly.
- Conduct regular awareness camps at the village level for patients and their families to undertand the implications of CKD and the available governmental assistance.
- To promulgate the use of technology by giving free smartphones for receiving medical reports, consulting the doctor using web apps, etc.

6 Conclusion

This paper is the first to statistically measure the impact of medical and welfare schemes of the Government of Andhra Pradesh in prohibiting the prevalence of CKD in Uddanam villages and the treatment provided to its patients in the past three years. This paper primarily identified that the majority of the current government schemes are targeted towards free dialysis to patients who are in advanced stages of the disease while a minor proportion is allocated to those in their early stages. Public policy and health measures to address the problem are herein proposed in concurrence with the opportunities and challenges of the region. Additionally, this paper presented the reach of both the government and technology in reaching the people directly for medical benefit.

Declarations

- Funding: Research Grant from Dr. Ambedkar Foundation, Ministry of Social Justice & Empowerment, Govt. of India

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- Ethics approval and consent to participate: Not applicable.
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- Data availability: Survey data is made available in raw format in Appendix **??**.
- Materials availability: Not applicable.
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- Author contribution:

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Effective Classification of Chronic Kidney Disease Using Extreme Gradient Boosting Algorithm

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ABSTRACT

With a high rate of morbidity and mortality, chronic kidney disease is a global health issue that also causes other diseases. Patients frequently overlook the condition because there aren't any evident symptoms in the early stages of CKD. An efficient and effective Extreme gradient boosting method for the early diagnosis of kidney illness has been proposed in this paper to explore the capability of various machine learning algorithms. DenseNet can extract a variety of features such as vector features. After that feature extraction phase, the data are fed into the feature selection phase. The features are selected based upon the Improved Salp swarm Algorithm (ISSA). The proposed CKD classification method has been simulated in PYTHON. Utilizing the CKD dataset from the UCI machine learning resources, the dataset is then tested. Sensitivity, accuracy, and specificity are the performance metrics used for the proposed CKD classification approach. The results of the experiments demonstrate that the proposed approach outperforms the present state-of-the-art method in classifying CKD.

KEYWORDS

Chronic Kidney Disease (CKD), CKD dataset, DenseNet, Improved Salp Swarm Algorithm (ISSA), Machine Learning, Classification, Outperform

INTRODUCTION

A serious death and illness problem is enforced by CKD, often known as CKD (Ammirati, 2020). It is one of the non-communicable diseases with one of the fastest expanding epidemiologies. CKD is a condition where the kidneys lose their ability to filter blood, allowing the body's waste products to build up within and leading to other health issues (Henry & Lippi, 2020; Jankowski et al., 2021; Byrne & Targher, 2020). Because clean, pure blood aids in the improved functioning of the body's organs, it is extremely vital to maintain healthy kidney function. Over many years, this harm develops (Portolés et al., 2020). Kidney function decreases as damage increases, which is bad for the body. In developing and underdeveloped nations, it is increasingly becoming a serious hazard. Diseases like diabetes and high blood pressure are the main causes of its onset (FIDELIO-DKD Investigators et al., 2021; Guzzi et al., 2019; Bidin et al., 2019). In addition to obesity, heart disease and a family history of CKD, other risk factors contribute to CKD.

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Testing may be the only way to determine whether the patient has the renal disease because, in its initial stages, CKD has no manifestations (Connaughton et al., 2019; Paik et al., 2022). Early identification of CKD in its initial phases can enable the patient to receive appropriate treatment and halt the development of ESRD (Zhuang et al., 2021). It is suggested that everyone with a risk factor for CKD, such as a family history of renal failure, high blood pressure, or diabetes, should be examined annually (Mihai et al., 2018). This illness is characterized by a gradual decline in renal function, which leads to a full loss of renal function in the end.

Early on, CKD does not manifest any overt symptoms. As a result, the disease might not be identified until the kidney has lost about 25% of its functionality (Kumar et al., 2022). Additionally, CKD affects the human body globally and has a high rate of morbidity and mortality. Cardiovascular disease may develop as a result (Han et al., 2020). A pathologic illness that progresses and cannot be reversed is CKD. Therefore, early detection and diagnosis of CKD are crucial for allowing patients to begin treatment and halt the disease's progression (Chen et al., 2019).

Diabetes, high blood pressure, and cardiovascular disease (CVD) are risk factors for CKD patients. Patients with CKD experience side effects, particularly in the late stages, which weaken the immunological and nervous systems (Sharma, 2018; Siraj, 2019). Patients may be in advanced stages in developing nations, necessitating dialysis or kidney transplants. Glomerular filtration rate (GFR), a measure of kidney function, is used by medical professionals to identify renal illness. Age, blood test results, gender, and other patient-related characteristics are taken into account while calculating GFR. Doctors can divide CKD into five stages based on the GFR value (Wang et al., 2019).

Machine learning describes a computer program that evaluates and extrapolates task-related data to determine the traits of the associated pattern (Gunasundari et al., 2018). This technology is capable of making cost-effective and accurate diagnoses of diseases, making it a potentially useful tool for CKD diagnosis (Calderon-Margalit et al., 2018). With the advancement of information technology, it has evolved into a new kind of medical instrument and has a wide range of potential applications.

The following are the contributions of the proposed research:

- The preprocessing stage includes checking for uneven data and estimating missing values as well as removing noise like outliers and normalization.
- Then the pre-processed data is given as the input into the DenseNet for feature extraction. In this process, the layers of DenseNet are utilized to extract the important features of the input data.
- The features are selected based on the Improved Salp swarm Algorithm.
- Then the selected features are passed into the classification phase. An extreme gradient boosting algorithm is used for classification. Whether the data is Ckd or not CKD.

The remaining portions of the paper are formatted as follows: The research on CKD classification will be covered in the part that follows. The suggested approach is explained in Section part 3. Portion 4 discusses the evaluation criteria and categorization techniques used. The research's findings are summarized in Part 5. In Part 6, comes to a close.

LITERATURE REVIEW

In this section, we review some existing Machine learning approaches for diagnoses of CKD.

Elhoseny et al. (2019) introduced DFS with the D-ACO algorithm for CKD. Before building the ACO-based classifier, the suggested intelligent system via DFS removes unnecessary or duplicate features. The effectiveness of the suggested algorithm is assessed utilizing a CKD dataset, and a comparison is also done with the other approaches. The suggested D-ACO algorithm exceeded the other approaches with increased categorization effectiveness in a number of ways when compared to the current approaches.

Jerlin Rubini and Perumal (2020) presented MKSVM and FFOA for disease classification. That is used to pick the best features. For the goal of classifying medical data, the processed and chosen features from the dataset are sent to the presented approach. The provided approach produces improved accuracy when compared to current approaches.

Ma et al. (2020) introduced the HMANN for the earlier detection and characterization of chronic renal failure on the IoMT platform. The suggested HMANN is categorized as an MLP and SVM using a Back Propagation (BP) technique. The strategy that is being shown helps to segment the renal image and eliminates noise. The suggested HMANN approach for kidney segmentation provides high accuracy while greatly lowering the time to outline the contour.

Chen et al. (2020) introduced the AHDCNN for the identification of kidney disease. The numerous sub-types of lesions in kidney cancer are distinguished from CT scans using a deep learning algorithm. First, the acquired data will be examined, along with any missing values. Utilizing the learning and activation mechanisms effectively is the best method to prevent kidney disease. These advances in machine learning provide a promising framework for finding clever solutions that can show their predictive relevance outside the context of kidney disease.

Linear regression (LR) and neural networks were introduced by Abdelaziz et al. (2019). (NN). Critical factors that have an impact on CKD are identified using LR. NN is employed to forecast CKD. Out of the twenty-four parameters that have an impact on CKD, thirteen are crucial, according to the trial data, and a hybrid intelligent model has a 97.8% accuracy rate.

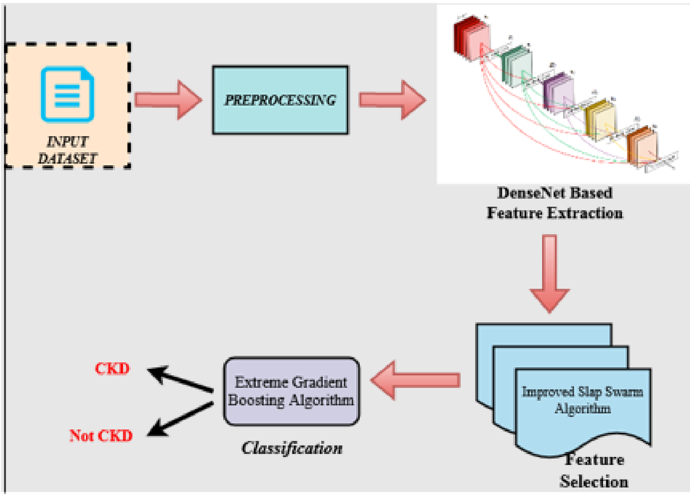
ANN and LR were recommended by Ahmed and Alshebly (2019) for the prediction of chronic renal disease. According to the experimental findings, the ANNs classifier performs better than the LR method. According to the elements that had the biggest influence on the data of patients with chronic renal illness, the variables creatinine and urea are the most significant and effective variables when applying the two approaches. Using FCM clustering, which is efficient in mining complicated data with fuzzy correlations among members, Kunwar et al. (2019) demonstrated analysis and identification of Chronic Kidney Disease.

PROPOSED METHODOLOGY

The proposed chronic kidney disease classification employing the Extreme gradient boosting algorithm is discussed in this section. The preprocessing processes are used to increase the classification efficiency even more. The raw data were passed through the preprocessing phase. Preprocessing tasks included checking for imbalanced data and approximating missing values as well as removing noise like outliers and normalization. Then the preprocessed raw data is fed into the feature extraction phase. The features can be extracted based on DenseNet. In this process, the layers of DenseNet are used to extract the important vector features of data. With the help of the Improved Salp swarm Algorithm, the features are selected, followed by classification is used. After the feature selection process, the Extreme gradient boosting algorithm is utilized to classify the CKD.

In our strategy, the work is processed based on four phases such as preprocessing, feature extraction, feature selection and classification. Figure 1 depicts the general structure of the proposed methodology.

Figure 1. Architecture diagram of proposed Methodology



PREPROCESSING

The most crucial step in obtaining the required features and classification levels is preprocessing the data. The data's quality must be good to provide efficient performances. The dataset needed to be cleaned up during preprocessing because it had outliers and noise. Estimating missing values, removing noise like outliers, normalizing, and verifying for imbalanced data were all parts of the preprocessing step. When patients are undergoing tests, it is possible for some measures to be missed, leading to missing numbers. 158 occurrences in the dataset were complete, whereas the rest instances had missing values.

Missing Values

The dataset comprised 158 cases that were fully finished, and the rest instances had missing values. The simplest way to deal with missing values is to remove the record, although this approach is problematic for small datasets. Instead of deleting records, we can apply algorithms to estimate the missing values. One the statistical measures, such as median, mean, and standard deviation, can be used to calculate the missing values for numerical features. But utilizing the mode technique, which substitutes the missing value with the most frequent value of the characteristics, it is possible to evaluate the missing values of nominal features.

FEATURE EXTRACTION

A robust diagnostic model cannot be built since the vector characteristics must be extracted to exclude features that are irrelevant and unhelpful for prediction. The pre-processed data is then fed into the DenseNet as input so that features can be extracted. The vector features of the data are extracted in this step using the DenseNet layers. A feed-forward neural network like DenseNet ensures maximal information flow across layers by directly connecting each layer to all succeeding layers. The dense block, transition layer, GAP, and convolutional layer are the primary components of the DenseNet structure.

Every layer passes its feature maps to all succeeding layers and receives extra input from all earlier layers. Concatenation is used to merge the resulting feature maps from the previous layer with those from the current layers. Each layer of the network is connected to all of the successive layers, and these networks are known as dense nets. Compared to conventional CNNs, this model requires fewer parameters. Additionally, it lessens the overfitting issue that smaller malware training sets have.

Dense Block

Considering the input data x_0 that the suggested convolutional network processes. Every layer of the network, which consists of N layers, performs a nonlinear transformation called F_n (.). Assume layer n is made up of the feature maps from all layers of convolution that came before it. Cascaded feature maps from layers 0 to n − 1 from the input data are shown $x_0,....,x_{n-1}$. As a result, this structure is connected to an N layer network via N (N + 1)/ 2 links. The n[th] layer's output can be calculated using:

$$x_n = F_n\left(\left[x_0,....,x_{n-1}\right]\right) \tag{1}$$

while F_n (.) is the composites functional of Batch Normalization (BN)- Rectified Linear (ReLU) Units, $\left[x_0,....,x_{n-1}\right]$ is a fusion of feature maps generated from 0 to n − 1 layer, and x_n is the present nth layer. ReLU, 3 × 3 convolutions, and BN are the subsequent processes in the transition layer (Conv). If the dimensions of the feature maps alter, the fusion procedure is not practical. The layers with various feature map sizes are consequently down sampled. Among two adjacent Dense Conv blocks, transition layers made up of 1× 1 Conv and 2 2 ×average pooling operations are provided. Seven by seven Conv blocks with a stride of two make up the first Conv layer.

BN is a widely accepted standard technique for achieving quick convergence and improved neural network classification capacity. The following output $\hat{x}_r$ can be provided for a short batch of data from B:

$$x_{BN} = \frac{\hat{x}_r - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{2}$$

$$\hat{x}_r = \gamma x_{BN+\beta} \tag{3}$$

Transition Layer

To speed up training and reduce the number of features, the transitional layer was used because dense connections enhanced network parameters. For every transitional layer in the tests, a 1×1 Conv layer for lowering the data size and a 2×2 average pooling were used. To guarantee the invariance of feature shift and scale, the input feature maps were divided into many, non-overlapping regions by the pooling layer, which then estimated the average value for each region.

As a result, the network processing was reduced while the important features were maintained, producing a more reliable model.

Gap Layer

We processed the feature maps with the GAP after combining dense blocks and transitional layers, and then we fed the processed feature maps into the next Softmax layer for categorization selections. Whenever GAP sets the window to the same dimensions as the feature map, the featured maps can be easily recognized as probability maps for categorization. This emphasizes the correlations among feature maps and categories. The training parameters were effectively decreased by generating the corresponding feature vector by averaging every feature map.

Softmax Classifier

The localization of MI was made possible in the current work by the training of the Softmax classifier using the feature vectors generated by DenseNet. For the dataset $\left\{\left(x_{GAP}^{(i)}, y^{(i)}; i \in 1 \ldots N, y^{(i)} \in 0, \ldots k-1\right)\right\}$ where $x^{(i)}$ GAP is the ith feature vectors of the input sample The categorization probability for every sample is provided by:

$$p(y^{(i)} = j \mid x_{GAP}^{(i)}; \theta) = \frac{e^{\theta_j^T} x_{GAP}^{(i)}}{\sum_{j=1}^{k} e^{\theta_j^T} x_{GAP}^{(i)}} \tag{4}$$

while $p(y^{(i)} = j \mid x_{GAP}^{(i)}; \theta)$ denotes the likelihood that the GAP falls under the jth category, which is identical to the likelihood that the GAP falls under one of the several types of MI. The following provides the Softmax classification function:

$$h_\theta\left(x_{GAP}^{(i)}\right) = \begin{bmatrix} p(y^{(i)} = 1 \mid x_{GAP}^{(i)}; \theta \\ p(y^{(i)} = 2 \mid x_{GAP}^{(i)}; \theta \\ \cdot \\ \cdot \\ \cdot \\ p(y^{(i)} = k \mid x_{GAP}^{(i)}; \theta \end{bmatrix} = \frac{1}{\sum_{j=1}^{k} e^{\theta_j^T} x_{GAP}^{(i)}} \begin{bmatrix} e^{\theta_1^T x_{GAP}^{(i)}} \\ e^{\theta_2^T x_{GAP}^{(i)}} \\ \cdot \\ \cdot \\ \cdot \\ e^{\theta_k^T x_{GAP}^{(i)}} \end{bmatrix} \tag{5}$$

while θ is the parameter and $\sum_{j=1}^{k} e^{\theta_j^T X_{GAP}^{(i)}}$ is the operation of the likelihood normalization.

FEATURE SELECTION

The choice of features will have a big impact on how accurate and complex the classifier is during judgment. Feature selection is used to increase insight into the profusion of data while also shortening the computing time and complexity of the prediction model. The improved salp swarm method provides a basis for feature selection.

Salp Swarm Algorithm (SSA)

The SSA is a heuristic algorithm that draws inspiration from the foraging behavior of slap swarms. In SSA, populations are split into two groups: leaders and followers. A leader location upgrade operator and a follower location upgrade operator make up the majority of SSA. The operator for updating the leader position is:

$$x_1^{t+1} = \begin{cases} x_{best}^t + c_1\left(\left(u_b - l_b\right)c_2 + l_b\right)c_3 \geq 0 \\ x_{best}^t - c_1\left(\left(u_b - l_b\right)c_2 + l_b\right)c_3 < 0 \end{cases} \tag{6}$$

$$c_1 = 2\exp\left(-\left(\frac{4t}{t_{max}}()^2\right)()\right) \tag{7}$$

while ub and lb stand for the search space's upper and lower limits, correspondingly, c2 and c3 stand for two random values, and tmax signifies the number of iterations, xt best represents the location belonging to the greatest food source at the t-th iteration. One way to express the follower's position upgrade operator is as follows:

$$x_i^{t+1} = \frac{1}{2}\left(x_i^t + x_{i-1}^t\right), \left(i \geq 2\right) \tag{8}$$

An Improved Slap Swarm Algorithm (ISSA)

Despite SSA having demonstrated its ability to be applied to real-world issues, the algorithm also has the drawback of being susceptible to local optimal solutions. In light of this, this work develops an ISSA by combining the chaotic local search (CLS) and Levy's flight (LF) strategies. The LF technique can be applied following Levi's distribution, which is usually assumed:

$$L\left(Z\right) \approx Z^{-1-\beta}, 0 < \beta \leq 2 \tag{9}$$

$$Z = \frac{A}{|\ B\ |^{1/\beta}}, A \approx N\left(0, \sigma^2\right), B \approx N\left(0, \sigma^2\right) \tag{10}$$

$$\delta^2 = \left\{\frac{\Gamma\left(1+\beta\right)}{\beta\Gamma(\left(1+\beta\right)/2}.\frac{\sin(\pi\beta/2)}{2^{\left(\beta-1\right)/2}}\right\}^{2/\beta} \tag{11}$$

z being the step size; β is the Levy index capable of regulating stability. $A \approx N\left(0, \sigma^2\right)$ Denotes a sample taken from a Gaussian distribution, and its average and standard deviation are both zero and δ2, accordingly. Γ (·) includes the Gamma function.

The CLS strategy is best described as:

$$v_{k+1} = 4v_k\left(1 - v_k\right), k = 1,2,\ldots n\left(v_1 \in \left(0,1\right), v_1 \neq 0.25, 0.5, 0.75\right) \tag{12}$$

$$x_{new}^{t+1} = \left(1 - S\right)x^{t+1} + S\left(l_b + \left(u_b - l_b\right)v_{k+1}\right) \tag{13}$$

$$S = 1 - \left(\frac{t-1}{t}\right)^{m} \tag{14}$$

where n is the number of steps in a random local search. The shrinking speed is managed by m. To obtain ISSA, integrate the LF and CLS strategies into the SSA. The following stages can be used to divide up ISSA implementation:

Phase 1: Initialization of the population:

$$x^{1} = \left(u_{b} - l_{b}\right) rand + l_{b}$$

a random number, rand, is used.

Phase 2: Updating the positions of the leading salp and follower salp using Equations (11) and (13).
Phase 3: Adopting the LF approach.

Upgrade the population using Equations (11) through (13), and then record the ideal response.

Phase 4: CLS approach implementation. A chaotic local search will be conducted by the phase three-acquired optimal solution. There are 8000 steps in a CLS. It should be emphasized that once a superior outcome is discovered using the CLS technique, CLS is terminated.
Phase 5: Ending the process. We additionally take into account two termination conditions to help ISSA converge to the global optimum:
Criteria 1: Completing the maximum number of iterations.
Criteria 2: Ensuring that the algorithm's objective function value changes by less than 10-6 after 50 iterations.

CLASSIFICATION

The final step of a model, categorization, is to predict the label. The most popular machine learning approach, the Extreme gradient boosting algorithm, is summarized in this portion.

Extreme Gradient Boosting Algorithm

The distributed gradient boosting algorithm known as XGBoost, sometimes known as extreme gradient boosting, has been developed to be very effective, adaptable, and portable. A group of classification or regression trees make up the decision tree ensemble-based XGBoost. It was established as an improved version of the gradient boosting technique and is a supervised machine learning approach based on ensemble learning. By aggregating the predictions of weak learners, the XGBoost algorithm uses additive approaches to create an effective learning approach. The XGBoost classifier avoids the overfitting issue and maximizes the use of computational resources in addition to its speed and great performance. These benefits come from the objective functions being made simpler so that they may be executed in parallel during the training phase and allow for the integration of regularization and predictive terms.

The first learner is fitted to the complete data according to the steps of the XGBoost algorithm. The second learner is then adjusted to include the previous learner's mistakes. Until a termination criterion is fulfilled, this process is continued, and when it is, the sum of all learners' predictions becomes the final prediction model. Equation (6) depicts the prediction procedure at the next stage:

$$f_i^{(t)} = \sum_{n-1}^{t} f_n\left(x_i\right) = f_i^{(t-1)} + f_t\left(x_i\right) \tag{15}$$

To begin with, the objective function is indicated as:

$$obj = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t)}\right) + \sum_{i=1}^{t} \Omega(f_i) \tag{16}$$

This equation has three variables: n, l, and Ω, which stand for the number of trees, training loss function, and regularization term, respectively. The XGBoost increases the loss function to the second order and gets rid of all constants to accomplish the goal that has been set for step t. As a result:

$$L^{(t)} = \sum_{i=1}^{n} \left[g_i f_t\left(x_i\right) + \frac{1}{2} h_i f_t^2\left(x_i\right) \right] + \Omega\left(f_t\right) \tag{17}$$

while the definitions of the gi and hi are:

$$\begin{cases} g_i = \partial_{\hat{y}_i(t-1)\left(y_i, \hat{y}_i^{(t-1)}\right)} \\ h_i = \partial^2_{\hat{y}_i^{(t-1)}} l\left(y_i, \hat{y}_{\substack{t-1 \\ i}}\right) \end{cases} \tag{18}$$

According to the decision rules for a particular tree, Ij is the instance set divided into the j-th leaf node. The score value for a tree's quality can be calculated using the formula (6). They also specified the point increase that results from splitting a leaf into two leaves:

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} \right] - \gamma \tag{19}$$

This equation is made up of the scores on the new left and right leaves, the original leaf's score, and the additional leaf's score after regularization. By scanning from left to right to obtain all feasible split options, we can quickly choose the best split by the highest Gain value:

$$\alpha\left(f\right) = \delta T + \frac{1}{2}\sigma\mu^2 \tag{20}$$

while σ is the regularization parameter, μ is the leaf node score vector, and δ is the minimal loss required to further divide the leaf node.

RESULT AND DISCUSSION

To illustrate the conclusion, using a benchmark dataset to compare the proposed method to existing methodologies in terms of sensitivity, specificity, precision and accuracy. The materials and metrics that were employed to achieve the intended results will be described in this paper. The proposed experiment's performance was evaluated in PYTHON using medical database. On an Anaconda navigator-equipped Windows 10 computer with 16 GB RAM and an Intel Ci7 64-bit processor, we trained and validate the proposed model. Tensor flow is used as the backend for all simulations, which are run on Keras.

DATASET DESCRIPTION

The UCI, which was gathered from hospitals and donated, is where the CKD data set that was used in this work was found. 400 samples make up the data collection. Every sample in this data set has 24 predictive factors, including a categorical response variable. Every class has two values: non-CKD and CKD (example with CKD). 250 of the 400 samples are classified as having CKD, while 150 are classified as not having CKD. It is crucial to note that the data contains a significant number of missing values. Table 1 contains a list of each variable's specifics.

Table 1. Dataset description

Variables	Explanation	Scale	Class	Missing Rate
Age	Age	Age in years	Num	2.25%
su	Serum creatinine	In mgs/dI	Num	4.25%
bp	Blood pressure	In mm/Hg	Num	3%
sod	Sodium	In mEq/L	Num	21.75%
al	Albumin	(0,1,2,3,4,5)	NOM	11.5%
pcv	Packet cell volume	-	Num	17.75%
pcc	Pus cell clumps	(present, not present)	NOM	1%
rbcc	Red blood cell count	In millions/cmm	Num	32.75%
ba	Bacteria	(present, not present)	NOM	1%
sg	Specific Gravity	(1.005,1.010, 1.015, 1.020, 1.025)	NOM	11.75%
bu	Blood urea	In mgs/dI	Num	4.75%
pc	Pus cell	(normal, abnormal)	NOM	16.25%
pot	Potassium	In mEq/L	Num	22%
rbc	Red Blood Cells	(normal, abnormal)	NOM	38%
hemo	Hemoglobin	In gms	Num	13%
su	Sugar	(0,1,2,3,4,5)	NOM	12.25%
htn	Hypertension	(yes, no)	NOM	0.5%
wbcc	White blood cell count	In cells/cumm	Num	26.5%

Table 1 contniued on next page

Table 1 continued

Variables	Explanation	Scale	Class	Missing Rate
dm	Diabetes mellitus	(yes, no)	NOM	0.5%
cad	Coronary artery disease	(yes, no)	Class	0.5%
ane	Anemia	(yes, no)	Num	0.25%
pe	Pedal edema	(yes, no)	Num	0.25%
class	Class	(ckd, not CKD)	Num	0%
appet	appet	(good, poor)	Num	0.25%
bgr	Blood glucose random	In mgs/dI	Num	11%

METRICS FOR EVALUATION OF THE MODEL

This stage involved assessing each technique's effectiveness to decide which could produce the best outcomes. Each approach used in this study was examined using the metrics of sensitivity, accuracy, and specificity from the confusion matrix. The True Positive is represented as TP, False Positive is represented as FP, True Negative is denoted as TN, and False Negative entries in the confusion matrix (FN).

Accuracy

The maximum number of positive outcomes divided by the maximum number of instances is used to calculate a model's accuracy:

$$Accuracy = \frac{TN + TP}{FP + TN + TP + FN} \tag{21}$$

Precision

By evaluating the actual positive effects of the projected ones, checks the model's accuracy. The ratio of accurately predicted positive items to all predicted things is:

$$Prescision = \frac{TP}{TP + FP} \tag{22}$$

Recall

Generated is the total number of actual positive values that the model noted and categorized as positive:

$$Recall = \frac{TP}{TP + FN} \tag{23}$$

F1-Score

Precision and recall are two functions of the F1 score. A precise-recall balance is required, in which case the balance is determined:

$$F1 = 2 \times \frac{precision \times Recall}{Precision + Recall} \tag{24}$$

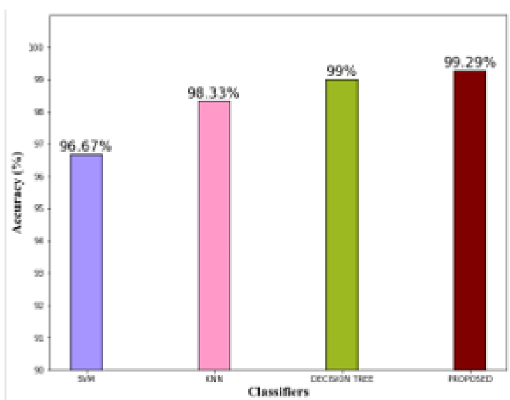
Evaluation Performances

The performances can be compared with the existing approaches like SVM, KNN, PNN and decision tree.

Table 2. Performance evaluation comparison with existing approaches

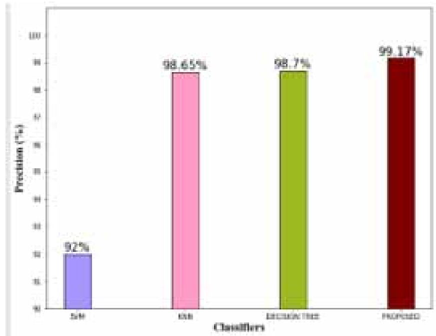
Classifiers	SVM	Decision Tree	KNN	Proposed
Accuracy	96.67%	99.17%	98.33%	99.29%
Precision	92%	98.79%	98.65%	99.17%
Recall	94.74%	98.68%	97.37%	98.97%
F1-Score	97.30%	99.34%	98.67%	99.65%

Figure 2. Accuracy performance over proposed with existing approaches



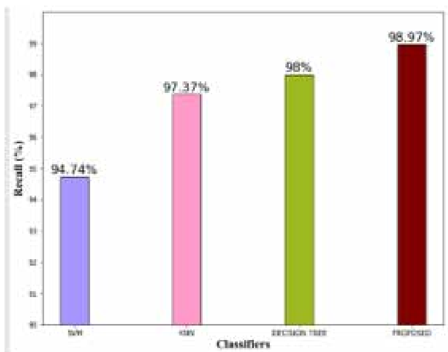
Performance evaluation comparison with existing approaches is shown in table 2. Comparison can be made with the approaches like SVM, decision tree, KNN. When differentiating the accuracy SVM gain 96.67%, the Decision tree yield 99.17%, KNN gains 98.33% and our proposed approach yield 99.29%. Accuracy performance over proposed with existing approaches is represented in figure 2.

Figure 3. Precision performance over proposed with existing approaches



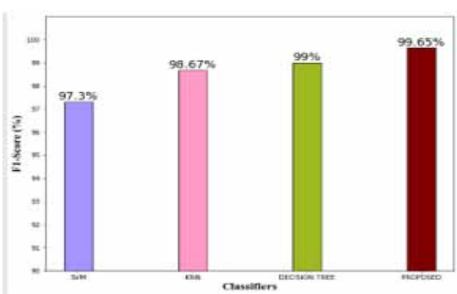
When differentiating the precision seen in figure 3, SVM gain 92%, the Decision tree yield 98.79%, KNN gains 98.65% and our proposed approach yield 99.17%. Precision performance over proposed with existing approaches.

Figure 4. Recall performance over proposed with existing approaches



When differentiating the precision in figure 4, SVM gain 94.74%, Decision tree yields 98%, KNN gains 97.37% and our proposed approach yield 98.97%. Recall performance over proposed with existing approaches.

Figure 5. F1-Score performance over proposed with existing approaches



When differentiating the F1-score in figure 5, SVM gain 97.3%, Decision tree yields 99%, KNN gain 98.67% and our proposed approach yield 99.65%. F1-Score performance over proposed with existing approaches.

Table 3. Performance of the suggested technique with different datasets

Name of the dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)
Cleveland data	96.03	98.7	92.80
Hungarian data	93.19	91.48	96.22
Switzerland data	95.12	97.6	94.78
Proposed dataset	99.16	98.96	98.37

Figure 6. Performance of the suggested technique with different datasets

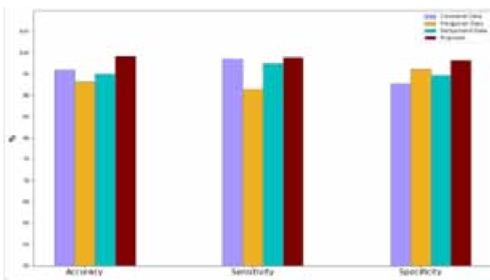
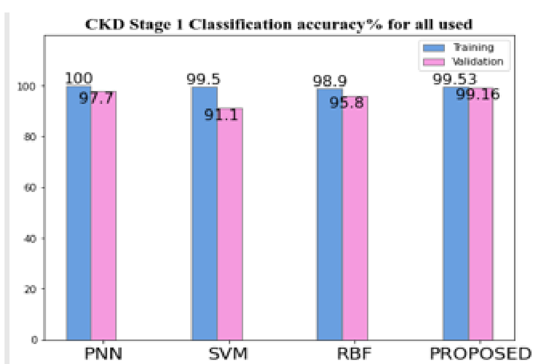


Table 3 displays the estimated values that were derived for four dataset records. These indicators can be used to forecast how effectively a model for classifying medical data will be generated. Four datasets accuracy percentages are 96.03%, 93.19%, 95.12%, and 99.16%. The four datasets sensitivity values are 98.7%, 91.48%, 97.6%, and 98.96%. 92.80%, 96.22%, 94.78%, and 98.37% are the specificity values for the four datasets. Figure 6 shows the performance of the suggested technique with different datasets.

Figure 7. Training and Validation Accuracy

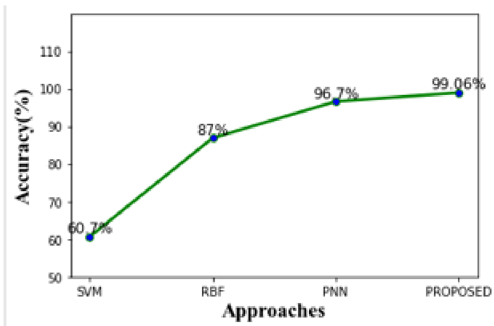


When comparing training and validation accuracy (table 4) with the existing approaches our proposed approach yield a greater accuracy which is depicted in figure 7.

Table 4. Accuracy and Execution Time comparison with existing approaches

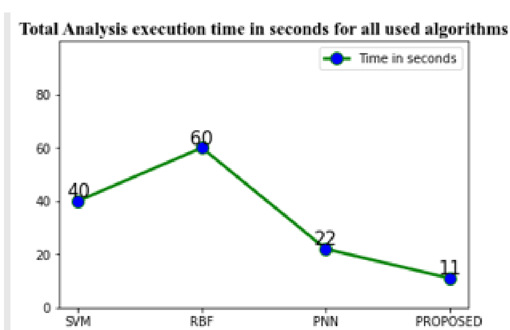
Approaches	Accuracy	Execution Time
SVM	60.7%	0:00:40
RBF	87%	0:00:60
PNN	96.7%	0:00:22
Proposed	99.06%	0:00:11

Figure 8. Performance Evaluation of Accuracy



Performance Evaluation of Accuracy is represented in figure 8. The Overall performances can be compared with the existing approaches like SVM, RBF and PNN. 60.7% of accuracy in SVM, 87% of accuracy in RBF, 96.7% of accuracy in PNN and the proposed approach yield a greater solution which is 99.06%. Performance Evaluation of Execution time is shown in figure 9.

Figure 9. Performance Evaluation of Execution time



CONCLUSION

The Extreme gradient boosting algorithm is described in this research for the classification of chronic kidney disease (CKD). On four scale datasets—the Cleveland dataset, the Hungarian dataset, the Switzerland dataset, and the CKD dataset—the anticipated work's outcome was evaluated by sensitivity, specificity, and accuracy. When differentiated from the existing RBF, PNN, and SVM, our proposed CKD categorization approach obtained the highest classification performance and also acquires maximum sensitivity and specificity. The suggested method thus achieves the kidney chronic dataset's maximum classification accuracy value of 99.06 percent. In future research projects, the clustering technique will be employed to increase classification accuracy and decrease instances of the wrong categorization.

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We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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AUTHORS' CONTRIBUTIONS

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

ETHICS APPROVAL

This material is the authors' own original work, which has not been previously published elsewhere. The paper reflects the authors' own research and analysis in a truthful and complete manner.

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A Hybrid Deep Learning Technique for Feature Selection and Classification of Chronic Kidney Disease

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Abstract: A significant global public health concern is the widespread presence of chronic kidney disease (CKD). High mortality rates are associated with the disease, particularly in developing nations. Since there are no visible early-stage signs, CKD frequently goes undiagnosed. In the meantime, preventing the disease from progressing requires early detection and prompt clinical care. To help clinicians discover CKD early, deep learning (DL) techniques can give an effective and affordable diagnosis. This research proposes a unique hybrid DL approach to classify CKD. In a pre-processing step, eliminate the missing values and reduce noise from data, data transformation, and outlier detection. After that, using the improved capsule network (Improved CapsNet) method to extract the features. Then, select essential features using the improved spotted hyena optimizer (ISHO) algorithm to better classification with less time. Finally, employ hybrid deep learning techniques of BConvLSTM and DNetCNN to classify the CKD. A recently introduced CKD prediction algorithm and well-known classifiers were used as benchmarks for the proposed approaches. The proposed model, which was trained with the smaller feature set, outperformed other classifiers with a classification accuracy rate of 99.89%. The experimental findings also demonstrate the positive effect of feature selection on the performance of the different techniques. The proposed technique has developed a reliable predictive system for recognizing CKD and may be extended to more unbalanced medical datasets to identify diseases reliably.

Keywords: Chronic kidney disease, BConvLSTM, DNetCNN, Improved spotted hyena optimizer (ISHO) algorithm, Improved capsnet, Deep learning.

Notations

S_j	Capsule Input
v_j	Capsule Output
W_{ij}	Weight Matrix
$U_{j/i}$	Predictive Vector
a_{ij}	Log-Likelihood
X	Current Iteration
$\vec{A}\vec{E}$	Co-Efficient Vectors
$\overrightarrow{P_q(x)}$	Prey's Location Vector
$\overrightarrow{P_q(x)}$	Spotted Hyena's Location Vector

1. Introduction

The high mortality rate of CKD has prompted a lot of attention. According to the world health organization (WHO), CKD has grown to be a problem that threatens developing nations. CKD is curable in its early stages but develops kidney failure in its last stages [1, 2]. Around the world, chronic kidney disease killed 800 million lives in 2022. The reason kidney illness is defined as a "chronic" condition is that it develops slowly over time and has an impact on the urinary system. Other health issues that have a variety of symptoms, including diabetes, low and high blood pressure, bone issues, and nerve damage, which result in cardiovascular disease, are brought on by the buildup of waste products in the blood [3-5]. Diabetes, cardiovascular disease (CVD), and blood pressure are challenging impacts for CKD-affected people. Patients may develop the disease in advanced phases in developing countries through kidney transplantation or necessitating dialysis [6, 7].

CKD can be protected from kidney failure with early detection and treatment. The easiest way to control CKD is to recognize it early, but waiting until it has progressed too far will result in kidney damage and the need for continuous dialysis or a kidney transplant to maintain everyday life [8–10]. Two medical procedures diagnose chronic kidney disease: blood or urine tests. CAD needs to support the diagnostic decisions made by doctors and radiologists because of the growing amount of patients with CKD, the shortage of specialists, and the high amount of treatment and diagnosis, particularly in developing nations [11, 12]. When implementing ML tasks, the techniques use the discriminative properties of the attributes to categorize the samples. The effectiveness of ML techniques depends not only on the selected technique but also on the characteristics of the input information [13-15]. Furthermore, not all input features may be equally significant in most ML applications, particularly in medical diagnosis. This lowers the computing cost of the model construction. To improve the proposed method's performance, we hybrid the novel deep learning techniques to classify chronic kidney diseases. The feature selection chooses necessary attributes to get less computation time. Hybrid deep learning techniques classify CKD. The main essential contribution of this research is,

- Missing variables, data transformation, encoding, and outlier recognition are done in a pre-processing step. To extract the features, use Improved CapsNet to extract the features from the dataset.
- Select the necessary attributes from extracted attributes utilizing the Improved Spotted Hyena Optimization (ISHO) algorithm to classify the CKD less quickly.
- To classify the chronic kidney disease into whether it’s CKD or not, employed hybrid techniques of BConvLSTM and DNetCNN.
- The evaluation performance is done with the CKD dataset and their attributes with accuracy, recall, specificity, precision, and f-measure metrics.

The other parts of the paper are arranged as follows. Section 2 discusses the related study on chronic kidney disease classification. Section 3 discusses in extensive detail the proposed technique and its parts. Section 4 describes the experimental approach. In section 5, the work is discussed, along with ideas for further research.

2. Literature survey

In this section, we mentioned some previous research papers based on CKD. Senan et al. [16] recommended using efficient categorization algorithms and recursive feature elimination methods to recognize CKD. In the pre-processing stage, they estimate missing variables and eliminate noise, such as normalization and outliers. Then, the recursive feature elimination (RFE) algorithm was used to identify the essential attributes by finding a high level of correlation between particular attributes and the targets. After that, the classification of the CKD utilizes four ML techniques (SVM, KNN, DT, RF).

A diagnostic recognition model for CKD was suggested by Hosseinzadeh et al. [17]. In this paper, they collected necessary data with smart multimedia medical devices and biomedical sensors. In a pre-processing step, they cleaned the collected data from any unnecessary noises and inconsistencies for the training and testing step in categorization performance. Then, select essential features to improve the effectiveness of learning algorithms. It finally used four different ML techniques, such as SVM, MLP, DT, and Naive Bayes, to classify chronic kidney diseases.

Early forecasting of CKD utilizing the deep belief network method was introduced by Elkholy et al. [18]. This paper introduced an intelligent categorization and forecasting model. First, they collect data from the UCI Dataset. After that, they remove the missing variables, reducing efficiency before analyzing the data. Finally, they used a modified deep belief network (DBN) as a categorization approach to forecasting kidney-related illness and the categorical cross-entropy as a loss function, and the Softmax as an activation function.

For the diagnosis and categorization of CKD, Elhoseny et al. [19] suggested the density-based feature selection (DFS) with ant colony based optimization (D-ACO) approach. The pre-processing step is the initial process since the database may contain noise and redundant information. Examining the information allows for several processes to be carried out, such as data cleansing, filling in for missing numbers, and deleting extraneous data, as both of these affect performance. There are 24 features in total in this work, some of which are chosen using DFS by repeatedly producing a set of attributes until DFS obtains the best subset; a wrapper approach was used to select the best feature subset. ACO-based categorization approach is used to categorize the data as to whether there is CKD or not having CKD to register the obtained feature vector.

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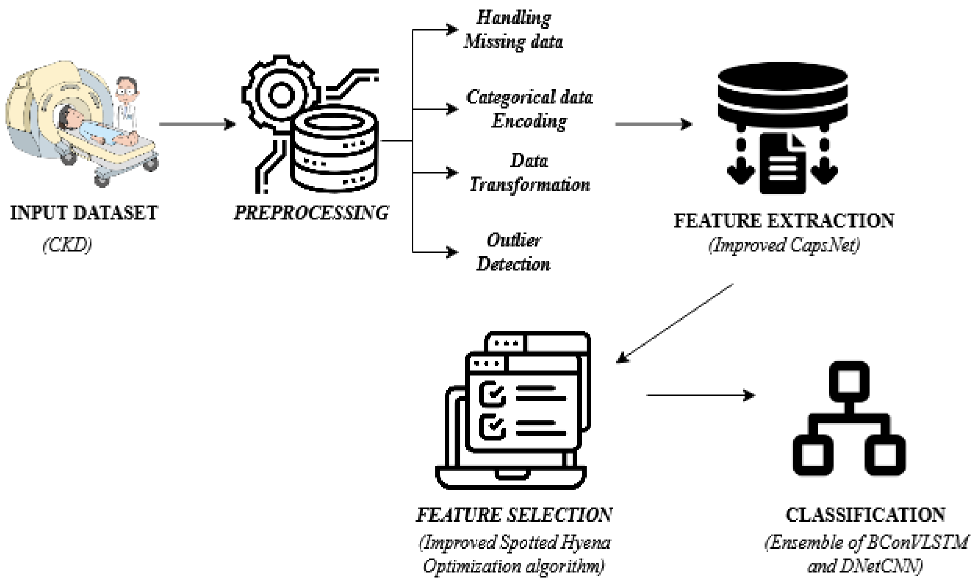

Figure. 1 The structure of the proposed work

To predict CKD based on cloud IoT, Abdelaziz et al. [20] suggested a hybrid intelligent model employing linear regression (LR) and neural network (NN), two intelligent techniques. Using LR, it is possible to identify significant variables that affect CKD. NN was employed to forecast CKD.

From the literature survey, they have some research problems to solve. The problems occur in literature studies,

- They did not perform topic modeling and accuracy is not significant.
- The machine learning algorithms might need more interpretability, making it easier for healthcare professionals to understand and trust the decision-making process.
- They didn't select any relevant features for CKD detection.
- The computation complexity of the research is high.

To overcome these problems, propose a novel deep-learning technique to achieve effective results in this research. A process on dataset data to estimate the missing values, remove noise, data transformation, and outlier detection is done in a pre-processing step. Then, select the essential features from extracted features to perform classification accurately with less computation time.

3. Proposed methodology

CKD has become a global burden, increasing mortality rates due to the lack of an adequate diagnosis system. Providing improved medical care for CKD patients while preserving people's lives is becoming more difficult these days. To address the CKD categorization problem, an efficient hybrid BConvLSTM and DNetCNN technique is developed in this research. The proposed technique involves the four essential steps previously discussed once the dataset was collected. It pre-processes handling missing data, transformation, categorial data encoding, and outlier recognition. Feature extraction is utilized to retrieve the features from the dataset. Feature selection is utilized to choose the necessary attributes. Categorization of CKD for improving recognition accuracy. The CKD information is pre-processed, then the attributes are extracted based on the improved CapsNet approach. And then, the attributes are chosen based on an improved spotted hyena optimization algorithm. Finally, the ensemble approach is proposed to classify the attributes into CKD or Non-CKD.

Fig. 1 demonstrates the structure of the proposed work.

3.1 Pre-processing

The pre-processing processes included the missing variables estimation and the elimination of noise. Some measurements during a patient evaluation could be absent or insufficient.

Handling missing values

In the data collection, 158 cases are complete, while the remaining ones are missing. The simplest method for handling missing variables is to ignore records, although this is impractical for small data sets. The data set is checked to see whether any attribute variables are missing. The statistical approach of mean computation was utilized to approximate the missing variables for the numerical attributes. The missing values of nominal characteristics were replaced using the mode approach.

Categorical data encoding

Category variables must be encoded into number variables because most DL techniques only accept numeric variables as input. The features of categories like "no" and "yes" are represented by the binary values "0" and "1".

Data transformation

The process of altering amounts on the same scale is known as data transformation, which is done to prevent one variable from overpowering the others. Otherwise, regardless of the unit of weight, learning algorithms interpret more significant variables as smaller and higher ones as lower. To enable additional processing, data transformations change the variables of a data set. The research involved uses a data normalization strategy to increase the accuracy of DL models. The transformed data has a mean of 0 and a standard deviation 1.

Outlier detection

Observational points that stand out from the rest of the data are known as outliers. Measurement variability may be the root cause of an outlier, or it may indicate an experimentation error. The deep learning algorithm's learning process can be distorted and misled by an outlier. It results in longer training times, lower model accuracy, and worse outcomes. This research employs the interquartile range (IQR)-based technique to eliminate outliers.

3.2 Feature extraction

After performing pre-processing, we used the CapsNet technique to extract the features from the dataset. The Improved CapsNet model, a feature extractor, is applied for improved classification performance. When attributes or variables are actively processed using a variable or attribute selection mechanism, the FV outcomes may have redundant or unneeded attributes. The entire performance of choosing a portion of the highly discriminant characteristics is called feature selection. The proposed research employs entropy to assess uncertain information and show signal unpredictability by exhibiting the model disorder.

An established CapsNet method describes hierarchical relationships and maintains object position and feature information in the data. The pooling layer receives helpful information from the information in the CNN method. The likelihood of the network learning minute details decreases when the information is transmitted to the next pooling layer. The neural result of the CNN approach also produces a scalar value. The CapsNets generate vector results of a similar size but with different routing; each capsule comprises multiple neurons. The variable of data is denoted by the vector route [22]. CapsNet uses the Eq. (1) specified vector activation function called squashing as an alternative.

$$v_j = \frac{\|s_j\|^2}{1+\|s_j\|^2}\frac{s_j}{\|s_j\|} \tag{1}$$

j and S_j stand for the total capsule input, and v_j stands for capsule output. When there is an item in the data, v_j it shrinks the long vector to one, and when there isn't, it chokes the shorter vector to zero.

In addition to the initial layer of CapsNet, the weighted amount of the forecasted vector $\left(U_{j/i}\right)$ in the capsule, as located in the lower layer, estimates the total input values of the capsuleS_j. A capsule from the lowest layer's outcome (O_i) and weight matrix (W_{ij}) are used to estimate the predictive vector$\left(U_{j/i}\right)$.

$$S_j = \sum_i b_{ij} u_{j/i} \tag{2}$$

$$u_{j/i} = W_{ij} O_i \tag{3}$$

Where b_{ij} stands for the coefficient determined by the dynamic routing technique and is determined by,

$$b_{ij} = \frac{\exp(a_{ij})}{\sum_k \exp(a_{ik})} \tag{4}$$

Where log-likelihood is denoted bya_{ij}. One is the correlation coefficient between capsules i and those in the top layer, while Softmax defines log prior likelihood. For determining the objects of a specific class that are present in CapsNet, a margin loss is offered and is evaluated as follows:

$$\begin{aligned} L_k = {} & T_k max[O, m^+ - \|v_k\|]^2 \\ & +\lambda[1 - T_k max[O, \|v_k\| - m^-]^2] \end{aligned} \tag{5}$$

When class k is present, the value of T_k is one. Additionally, $m^+ = 0.9$ and $m^- = 0.1$ represent the weight of the loss and the hypervariable, respectively.

3.3 Feature selection

After extracting the features, it is necessary to find the essential components that have a strong and positive connection with attributes of importance for disease recognition. A robust recognition technique cannot be built since the vector features must be retrieved to exclude attributes that could be more helpful and relevant for forecasting. The improved spotted hyena optimizer (ISHO) algorithm is well known for its simplicity of use, adaptability to various settings, and efficiency in picking features from training datasets pertinent to forecasting target variables and removing weak attributes. The ISHO approach chooses the essential attributes by identifying high correlations between particular attributes and the target.

3.3.1. Improved spotted hyena optimizer (ISHO)

Large carnivorous canines, known as spotted hyenas, can be found in various open, arid habitats. Spotted hyenas feast on large and medium-sized herbivores, including wildebeests, impalas, and zebras. The spotted hyena is a highly sociable and clever animal. They use a variety of senses to recognize relatives and other people [23]. The connections between people of the same race were also ranked. In a population, trust is prioritized for those with high status.

3.3.1.1. Encircling prey

Spotted hyenas can locate their prey and encircle them. Due to the unknown search space, the spotted hyena closest to the prey is now the best contender. Following the determination of the optimum search solution, the locations of each other search agents are updated.

The below equations represent the mathematical description of this behavior:

$$C_h = \left|\vec{A}.\overrightarrow{P_q(z)} - \overrightarrow{P(z)}\right| \tag{6}$$

$$\overrightarrow{P(z+1)} = \overrightarrow{P_q(z)} - \vec{E}\cdot\overrightarrow{D_h} \tag{7}$$

Following is a computation of the vectors B and E:

$$\vec{A} = 2.\overrightarrow{rd_1} \tag{8}$$

$$\vec{E} = 2\vec{h}\cdot\overrightarrow{rd_2} - \vec{h} \tag{9}$$

$$\vec{h} = 5 - \left[iteration\frac{5}{MAX_{iteration}}\right] \tag{10}$$

3.3.1.2. Hunting

Spotted hyenas usually hunt in packs, rely on a group of reliable allies, and are good at spotting their prey. To update their location, other search agents should move in the direction of the best search agent. In this mechanism, the following equations are provided:

$$\overrightarrow{C_h} = \left|\vec{A}\cdot\overrightarrow{P_h} - \overrightarrow{P_k}\right| \tag{11}$$

$$\overrightarrow{P_k} = \overrightarrow{P_h} - \vec{E}\cdot\overrightarrow{C_h} \tag{12}$$

$$\overrightarrow{S_h} = \overrightarrow{P_k} + \overrightarrow{P_{k+1}} + \cdots + \overrightarrow{P_{k+N}} \tag{13}$$

The letters define the $\overrightarrow{P_{k+1}}$ $\overrightarrow{P_h}$ other spotted hyenas, which designate the location of the first best-spotted hyena. Here, N stands for the number of spotted hyenas, and its value is calculated as follows:

$$N = count_{nos}\left(\overrightarrow{P_h}, \overrightarrow{P_{h+1}}, \overrightarrow{P_{h+2}}, \cdots, \overrightarrow{P_h} + \vec{M}\right) \tag{14}$$

While nos specify the number of options and calculate all candidate options that are very similar when added to the best optimal answer found during the search, a random vector named $\vec{M}$ has a value between [0.5, 1].

3.3.1.3. Attacking prey (Exploitation)

The vector's value is reduced to create a mathematical model for attacking the target. To adjust the vector's value, which throughout iterations can go from 5 to 0, the variation in the vector is also reduced. When $E_j > 1$, a pack of spotted hyenas charges its victim. The following is the formula for attacking the prey mathematically:

$$\overrightarrow{P_{(z+1)}} = \frac{\overrightarrow{C_h}}{N} \tag{15}$$

Where the best search agent is located, other search agents are updated to reflect that location, and the best solution is recorded. With the help of the SHO approach, search agents can alter their locations and move closer to the target.

3.3.1.4. Search for prey (Exploration)

The position of the spotted hyenas in vector $\overrightarrow{C_h}$ spotted hyenas mostly hunt for prey. They avoid one another so they can hunt and attack their prey. When$E_j > 1$, spotted hyenas should depart from their prey. The system enables SHO to conduct international searches. A further element of SHO is $\vec{A}$ it enables exploration. The $\vec{A}$ vector in Eq. (15) contains the random value determining the prey's weight.

3.4 Classification

A hybrid deep learning technique is used to classify CKD. Here, we employed Bi-Directional Convolutional Long-Short Term Memory and DarkNet convolutional neural network. The data's global, long-term spatiotemporal characteristics are not altered when a ConvLSTM layer is added to the intermediate representations' spatial scale. Throughout the LSTM's recurrent operation, this encoding requires performed. A learned temporal representation is produced by a conventional LSTM network, which vectorizes and encodes its input through fully connected layers. These fully connected layers cause a loss of spatial information. Therefore, a convolutional rather than a fully linked operation may be preferred to maintain such spatial information. The ConvLSTM achieves that. It substitutes convolutional layers for the fully connected layers in the LSTM.

3.4.1. Bi-directional convolutional long-short-term memory (BConvLSTM)

Bi-Directional Convolutional Long-Short Term Memory (Bi-C-LSTM) is an LSTM neural network architecture variant incorporating convolutional layers and bidirectional processing. It combines the strengths of CNNs and LSTMs to capture spatial and temporal dependencies in sequential data. An extended recurrent neural network (RNN) is an LSTM, which can better consider time dependency [24]. Because LSTM cannot incorporate spatial correlation, ConvLSTM can address this issue. Both input-to-state and state-to-state transitions are subject to convolution procedures. ConvLSTM has a forget gate, an output gate, a memory cell, and an input gate, the same as LSTM. ConvLSTM can be expressed in the following way:

$$i_t = \sigma\left(A_{x_i}X_t + A_{h_i}H_{t-1} + A_{c_i}C_{t-1} + b_i\right) \quad (16)$$

$$f_t = \sigma\left(A_{x_f}X_t + A_{h_f}H_{t-1} + A_{c_f}C_{t-1} + b_f\right) \quad (17)$$

$$C_t = f_t o C_{t-1} + i_t tanh\left(A_{x_c} * X_t + A_{h_c} * H_{t-1} + b_c\right) \quad (18)$$

$$o_t = \sigma\left(A_{x_o}X_t + A_{h_o}H_{t-1} + A_{c_o}oC_t + b_c\right) \quad (19)$$

$$H_t = o_t otanh(C_t) \quad (20)$$

The convolution operation is represented by$*$, and Hadamard product by o . In contrast to ConvLSTM, which only employs forward data dependencies, BConvLSTM utilizes both backward and forward ConvLSTMs to perform the input data. The backward and forward information dependence can enhance the performance of predictions.

$$Y_t = tanh\left[A_y^{\vec{H}} \cdot \vec{H} + A_y^{\overleftarrow{H}} \cdot \overleftarrow{H} + b\right] \quad (21)$$

Tanh is a nonlinear function that is utilized to combine the result.

3.4.2. Darknet convolutional neural network (DNetCNN)

After selecting the essential features, we employ a new deep learning technique DNetCNN to categorize the CKD into whether it’s CKD or non-CKD. CNN is the best classifier among the many DL techniques. To increase the classification accuracy of the classifying CKD, the DNetCNN framework is utilized in this research. The activation function activates five pooling layers, 19 convolutional layers, and the darknet structure as an entire entity. The function of sigmoid activation is utilized for binary categorization [25]. The Softmax activation function is utilized in multi-classification. The 2D convolutional process is carried out with Eq. (22) for the input data X and kernel K.

$$C(X,K)_{(i,j)} = \sum_r \sum_c K(r,c) \times X \times (i-r, j-c) \quad (22)$$

Step parameterized input matrix for K. Given that the testing dataset for CKD uses a binary classification with Eq. (23), the sigmoid function is utilized in the proposed DNetCNN as an activation function.

$$Sigmoid(h) = \frac{1}{1+e^{-X_i}} \quad (23)$$

There were 16 convolution layers in the proposed DNetCNN. One convolutional layer comprising the activation and convolution procedures was present in every darknet layer. The follow-up of the three successive forms was the same for every of the four convolution layers. Standardizing the input data due to the convolution layer's typical operation reduced training time. The Maxpool operation in the pooling layer was carried out using the 2*2 formula. The region that the filters employed will be maximized. The filter sizes ranged from 8, 16, 32, and 64 from the darknet to the convolution layer. Fig. 3 depicts the proposed DNetCNN's layered architecture. The first layer was the darknet layer with a 3*8 filter. Then followed DN, pool, then CNN in that order. The filter value of the last convolution layer was 256. Using the DNetCNN technique classified CKD accurately. It achieved higher classification accuracy with less computation time.

Pseudo-code

BEGIN
1. Importing a CKD data set
2. Fill in the blanks and eliminate outliers
3. Convert text into numerical values
4. Adjust the data scale
5. Make use of the ISHO 'Feature Selection
6. FOR FEATURE SELECTION METHODS:
7. Choose the most essential features.
8. Make a list of the essential features.
9. Count the number of times each feature appears.

END FOR

10. Provide the proposed model with a list of features.
11. Set the model hyperparameters
12. Assign different validation scores to the scoring
13. Train using the proposed model
14. Sort data into CKD and non-CKD categories
15. Validation score

END

4. Results and discussion

In this part, the results of the proposed approach are reported. In Table 1, the hyperparameter settings for the proposed models are displayed. Figure 8 displays the confusion matrices. It proves the provided model successfully classified all actual positive and actual adverse events. The CKD class reports recall, accuracy, f-measure, and precision.

4.1 Experimental setup

Different environments have been utilized in the system's development. The environment configuration for the evolving system is displayed in Table 2.

Table 1. Settings for hyper-parameters

Hyper-Parameter	Setting
Batch size	15
Epochs	850
Activation Function	Relu
Optimizer	Adam
Dropout rate	0.5 to 0.1
Loss	Binary_Crossentropy
Activation output layer	Sigmoid

Table 2. The proposed system's environment setup

Resource	Details
RAM	8 GB
CPU	Core i5 Gen6
Software	Python
GPU	4 GB

Table 3. Splitting dataset

Dataset	Numbers
Testing and validation	100 patients
Training	300 patients

4.2 Dataset description

Data on CKD were gathered via the university of california irvine (UCI) Repository. The data set contains 400 patient records, some needing more specific values. It consists of 24 clinical attributes that show up in the prognostic of CKD, with a class attribute acting as an outcome of the patient being expected to have CKD. The expected attribute diagnostic has two values: "ckd" and "non-ckd." One hundred fifty values from the "non-ckd" class (37.5%) and 250 values from the "ckd" class (62.5%) are both included in the data set. (Source: https://www.kaggle.com/datasets/mansoordaku/ckdisease)

Splitting dataset: The dataset was split into 25 for testing and validation and 75% for training. The split data are displayed in Table 3.

4.3 Evaluation metrics

The accuracy of the proposed approach was computed by setting the non-CKD class value to zero and the CKD class value to one. True positives asserts that CKD has been correctly classified. The results of the false negatives test demonstrate that CKD was miscategorized. A false-positive result (FP) shows that the non-CKD samples were not correctly detected. True negative (TN) samples were correctly labeled as not having CKD.

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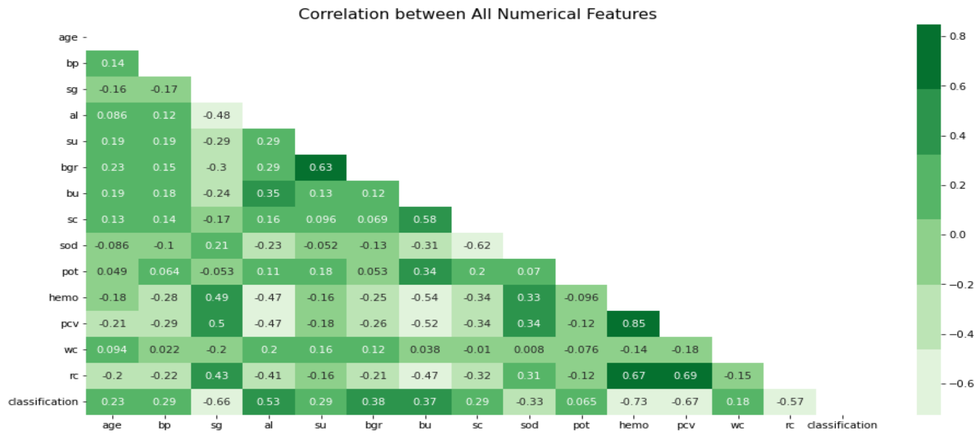

Figure. 2 Correlation between several features

4.3.1. Accuracy

It is the ratio of accurate estimates to all forecasting. The capacity to predict outcomes accurately can be used to define accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (24)$$

4.3.2. Recall

The following equation demonstrates how recall determines the ratio of correctly anticipated positive observations.

$$Recall = \frac{TP}{TP+FN} \qquad (25)$$

4.3.3. Precision

This metric denotes the ratio of correctly forecasted positive observations to all optimistic predictions, as shown in the equation below.

$$Precision = \frac{TP}{TP+FP} \qquad (26)$$

4.3.4. F-measure

In the F-measure, recall and precision are weighted and averaged. The method involves both false negatives and false positives. The term "F-Measure" is defined as

$$F - Measure = \frac{2\times(Precision\times Recall)}{(Precision+Recall)} \qquad (27)$$

The range of F-measure values is 0 to 1.

4.4 Performance metrics

The performance of the proposed method is to classify chronic kidney disease accurately with a higher classification accuracy level. Correlation is a statistical measure that quantifies the connection between two or more attributes. It indicates how changes in one attribute are combined with changes in another. The correlation coefficient, often defined as "r," ranges from -1 to 1, where 0 indicates no correlation, 1 indicates a strong positive correlation, and -1 indicates a strong negative correlation.

A dataset can be used to calculate the correlation between different traits or variables. The degree and direction of the association between features can be understood using correlation analysis. A positive correlation indicates that the two variables rise as one increases. When two variables are negatively correlated, one variable tends to increase while the other tends to decline. The absence of correlation indicates no consistent connection between the variables. Fig. 2 illustrates the adjustment between several dataset features.

4.5 Feature selection results

The proposed feature selection approaches are compared with other approaches in this section. Accuracy, recall, and specificity are used as evaluation criteria. Previous feature selection techniques are utilized, such as CFS+SVM, MIFS+SVM, RFS+SVM, Relief + CSF+ SVM, and RFP+SVM. The comparison of feature selection methods is shown in Table 4.

Table 5 compares existing and proposed classification techniques for CKD dataset analysis. Compared to other techniques, the proposed method achieved higher accuracy values, such as 99.89% of accuracy, 100% of recall, 99.85% of precision, and 99.82% of f-measure. Still, the existing method SVM obtained lower values of 92% of accuracy, 87% f recall, 96% of precision, and 92% of f-measure.

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Table 4. Comparison of feature selection approaches

Feature Selection Technique	**Total no of features**	**Selected features**	**% of features eliminated**	**Acc (%)**	**Rc (%)**
Correlation feature selection +SVM	22	11	50	92.71	94.83
Mutual information-based Feature selection +SVM	22	12	45.45	94.79	93.55
Relief Feature selection +SVM	22	8	63.63	89.61	93.33
ReliefF +CFS+SVM	22	7	68.18	91.67	93.22
R_FP-SVM	22	7	68.18	98.50	98.22
Proposed	22	10	70	99.89	100

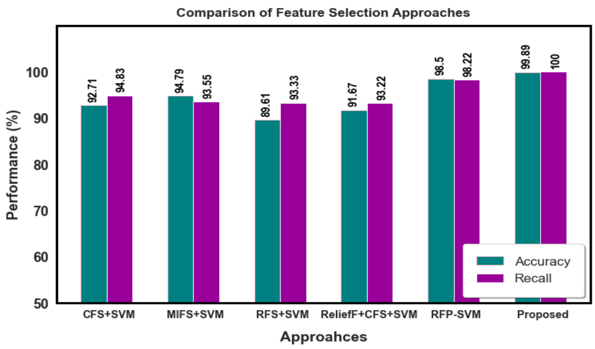

Figure. 3 Graphical representation of feature selection approaches

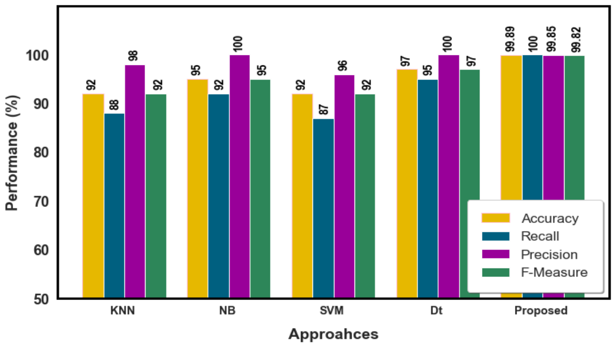

Figure. 4 Comparative analysis of classification techniques of proposed and existing techniques

Table 5. Comparison of the proposed model to the dataset for CKD's existing classification methods

Method	**Accuracy (%)**	**Recall (%)**	**Precision (%)**	**F-Measure (%)**
K-Nearest Neighbor (KNN)	92	88	98	92
Naïve Bayes (NB)	95	92	100	95
Support Vector Machine (SVM)	92	87	96	92
Decision Tree (DT)	97	95	100	97
Proposed	99.89	100	99.85	99.82

Table 6. Comparison of the proposed technique with other techniques from the literature used with the UCI dataset

Authors	**Model**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F-Measure (%)**
Senan et al. [16]	SVM	97.3	94.74	92	96.67
Hosseinzadeh et al. [17]	DT	97	95	99	-
Elkholy et al. [18]	DBN	98.52	-	-	87
Elhoseny et al. [19]	D-ACO	95	93.33	96	96
Abdelaziz et al. [20]	LR+NN	97.8	96.2	100	98.1
Proposed	BConvLSTM +DNetCNN	99.89	99.85	100	99.82

The comparative analysis of the existing and proposed methods is shown in Fig. 4 as a graph representation.

We compare various approaches with our proposed method. Table 6 shows how our proposed technique achieved the highest effectiveness and increased the detection rate. The proposed technique operates accurately with the dataset.

Table 6 lists the results for SVM, DT, DBN, D-ACO, AlexNet, LR+NN, and the proposed BConvLSTM+DNetCNN on the Dataset in terms of accuracy. The proposed technique achieved higher categorization accuracy than others.

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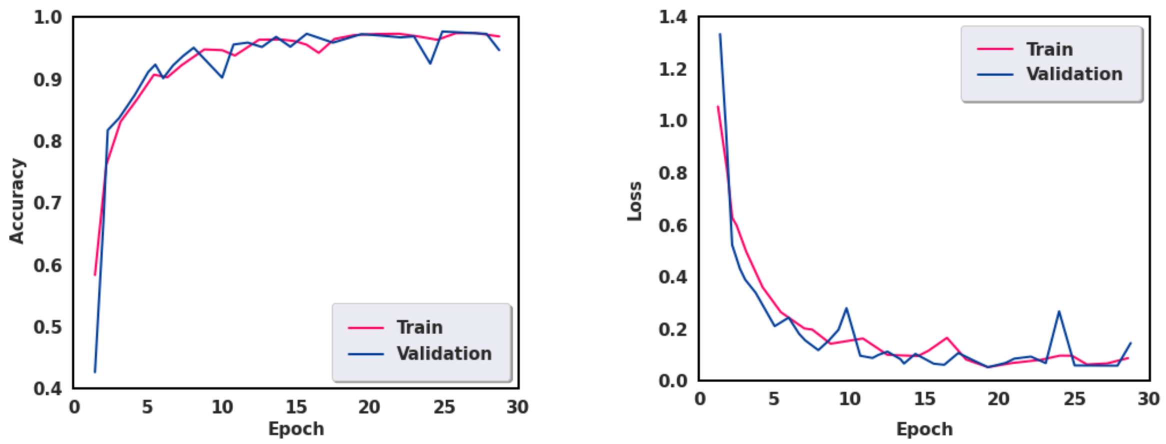

(a) (b)

Figure. 6: (a) Accuracy for testing and training and (b) Testing and training loss for the UCI CKD dataset

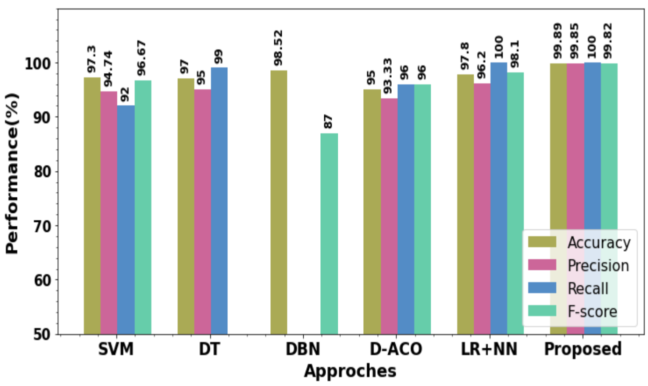

Figure. 5 Comparison of proposed with previous techniques

Table 7. Utilizing the proposed and previous methods

Methods	Computation Time
Senan et al. [16]	0.23
Hosseinzadeh et al. [17]	0.19
Elkholy et al. [18]	0.21
Elhoseny et al. [19]	0.25
Abdelaziz et al. [20]	0.17
Proposed	0.14

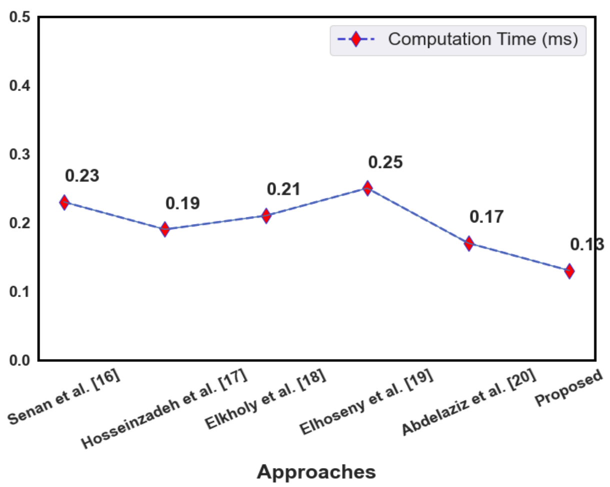

Figure. 7 The computation time of proposed and previous techniques

The achieved accuracy for the proposed technique is 99.89%, compared to SVM at 96.67%, DT at 97%, DBN at 98.5%, D-ACO at 95%, and LR+NN at 97.8%. Fig. 5 shows the comparison of the proposed approach with the existing approach.

4.6 Evaluation of training and testing

As the number of iteration steps increased, a graph of loss value and classification accuracy is shown in Fig. 6. The graph demonstrates that the method discussed in this study positively impacts convergence. The dataset was divided into testing and training phases. The processed training set is used in the training phase to train the proposed methods for 200 iterations. The learning rate is currently at 0.1.

4.7 Computation time

The error and computational time of the selected classifier serve as performance indicators. For classification accuracy, precision and recall will be considered. Each classifier takes into account the computing time. The proposed BConvLSTM+DNetCNN method achieves good recall, f-measure, and accuracy with low computation time. The proposed BConvLSTM+DNetCNN system's computing time is shown in Fig. 7.

Our proposed method achieved higher prediction accuracy and less computation time than previous techniques.

5. Conclusion and future scope

Chronic kidney disease (CKD) is a long-term condition in which the kidneys cannot function properly. It is a progressive condition that worsens over time, often leading to permanent kidney damage and declining kidney function. In this work, we proposed a unique hybrid DL approach to classify CKD. In a pre-processing step, eliminate the missing values and reduce noise from data, data transformation, and outlier detection. After that, it uses the improved capsule network (Improved CapsNet) method to extract the features. Then, select essential features using the improved spotted hyena optimizer (ISHO) algorithm to better classification with less time. Finally, employ hybrid deep learning techniques of BConvLSTM and DNetCNN to classify the CKD. The performance of the proposed model achieved 99.89% accuracy with less computation time. The future scope will develop a hybrid technique with an optimization algorithm to increase the accuracy of disease identification before the condition reveals itself in humans.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions

Conceptualization, Ramya Asa Latha Busi and James Stephen Meka; methodology, P V G D Prasad Reddy; software, Ramya Asa Latha Busi; validation, Ramya Asa Latha Busi, James Stephen Meka and P V G D Prasad Reddy; formal analysis, James Stephen Meka; investigation, P V G D Prasad; resources, James Stephen Meka; writing—original draft preparation, Ramya Asa Latha Busi; writing—review and editing, P V G D Prasad.

Acknowledgment

We declare that this manuscript is original, has not been published before, and is not currently being considered for publication elsewhere.

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(57) Abstract :
[036] The present invention relates to a novel deep learning technique to identify chronic kidney disease (CKD) through effective feature selection and classification. The invention introduces a technique to predict chronic kidney disease. There are five steps to achieving it. First, in the pre-processing stage, remove missing values and normalize the data while reducing noise. Then, employ the EfficientNet V2 approach to extract the features. The Binary Dandelion Algorithm (BDA) must be used to choose the necessary features once features have been extracted to speed up classification evaluation. Then, using the HMLSTM approach, determine whether the person has CKD. We employed the Lion Swarm Optimization Algorithm (LSOA) to increase forecast accuracy. The dataset on chronic renal illness provides the data we need for the experiment. The evaluation performance of the proposed method achieved 99.92% accuracy with less computation time compared to other existing techniques. The proposed method overcome the previous literature issues using feature selection technique and optimization algorithm. In the future, we will develop a hybrid technique with an optimization algorithm to increase the accuracy of disease identification before the condition reveals itself in humans.

No. of Pages : 29 No. of Claims : 10

"**FORM 1** THE PATENTS ACT 1970 (39 of 1970) and THE PATENTS RULES, 2003 **APPLICATION FOR GRANT OF PATENT** (See section 7, 54 and 135 and sub-rule (1) of rule 20)				(FOR OFFICE USE ONLY)	
			Application No.		
			Filing date:		
			Amount of Fee paid:		
			CBR No:		
			Signature:		
1. APPLICANT'S REFERENCE / IDENTIFICATION NO. (AS ALLOTTED BY OFFICE)					
2. TYPE OF APPLICATION [Please tick (✓) at the appropriate category]					
Ordinary (✓)		Convention ( )		PCT-NP ( )	
Divisional ( )	Patent of Addition ( )	Divisional ( )	Patent of Addition ( )	Divisional ( )	Patent of Addition ( )
3A. APPLICANT(S)					
Name in Full		Nationality	Country of Residence	Address of the Applicant	
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3B. CATEGORY OF APPLICANT [Please tick (✓) at the appropriate category]					
Natural Person ()		Other than Natural Person			
		Small Entity (✓)		Startup ()	Others ()
4. INVENTOR(S) [Please tick (✓) at the appropriate category]					
Are all the inventor(s) same as the applicant(s) named above?		Yes ()		No (✓)	
If "No", furnish the details of the inventor(s)					
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3. Prof. Prasad Reddy P.V.G.D.	Indian	India	Senior Professor, Department of CS & SE, A.U. College of Engineering (A), Andhra University, Visakhapatnam, Andhra Pradesh, India. Pin Code: 530003

5. TITLE OF THE INVENTION

"A Novel Deep Learning Technique to Identify Chronic Kidney Disease (CKD) through Effective Feature Selection and Classification"

6. AUTHORISED REGISTERED PATENT AGENT(S)	IN/PA No.	
	Name	
	Mobile No.	
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~~8. IN CASE OF APPLICATION CLAIMING PRIORITY OF APPLICATION FILED IN CONVENTION COUNTRY, PARTICULARS OF CONVENTION APPLICATION~~

~~Country~~	~~Application Number~~	~~Filing date~~	~~Name of the applicant~~	~~Title of the invention~~	~~IPC (as classified in the convention country)~~

~~9. IN CASE OF PCT NATIONAL PHASE APPLICATION, PARTICULARS OF INTERNATIONAL APPLICATION FILED UNDER PATENT CO-OPERATION TREATY (PCT)~~

~~International application number~~	~~International filing date~~

~~10. IN CASE OF DIVISIONAL APPLICATION FILED UNDER SECTION 16, PARTICULARS OF ORIGINAL (FIRST) APPLICATION~~

~~Original (first) application No.~~	~~Date of filing of original (first) application~~

~~11. IN CASE OF PATENT OF ADDITION FILED UNDER SECTION 54, PARTICULARS OF MAIN APPLICATION OR PATENT~~

~~Main application/patent No.~~	~~Date of filing of main application~~

12. DECLARATIONS

i) Declaration by the inventor(s)

(**In case the applicant is an assignee**: the inventor(s) may sign herein below or the applicant may upload the assignment or enclose the assignment with this application for patent or send the assignment by post/electronic transmission duly authenticated within the prescribed period).

I/We, the above named inventor(s) is/are the true & first inventor(s) for this Invention and declare that the applicant(s) herein is/are my/our assignee or legal representative.

(a) Date 02/09/2023

(b) Name	(c) Signature
1. Prof. James Stephen Meka 2. Mrs.Ramya Asa Latha Busi 3. Prof. Prasad Reddy P.V.G.D.	Ramya

~~(ii) Declaration by the applicant(s) in the convention country~~

~~**(In case the applicant in India is different than the applicant in the convention country:** the applicant in the convention country may sign herein below or applicant in India may upload the assignment from the applicant in the convention country or enclose the said assignment with this application for patent or send the assignment by post/electronic transmission duly authenticated within the prescribed period)~~

~~I/We, the applicant(s) in the convention country declare that the applicant(s) herein is/are my/our assignee or legal representative.~~

~~(a) Date~~

~~(b) Signature(s)~~

(c) ~~Name(s) of the signatory~~

(iii) Declaration by the applicant(s)

I/We the applicant(s) hereby declare(s) that: -

- ~~I am/~~ We are in possession of the above-mentioned invention.
- The ~~provisional~~/complete specification relating to the invention is filed with this application.
- ~~The invention as disclosed in the specification uses the biological material from India and the necessary permission from the competent authority shall be submitted by me/us before the grant of patent to me/us.~~
- There is no lawful ground of objection(s) to the grant of the Patent to me/us.
- ~~I am~~/we are the true & first inventor(s).
- ~~I am/we are the assignee or legal representative of true & first inventor(s).~~
- ~~The application or each of the applications, particulars of which are given in Paragraph-8, was the first application in convention country/countries in respect of my/our invention(s).~~
- ~~I/We claim the priority from the above mentioned application(s) filed in convention country/countries and state that no application for protection in respect of the invention had been made in a convention country before that date by me/us or by any person from which I/We derive the title.~~
- ~~My/our application in India is based on international application under Patent Cooperation Treaty (PCT) as mentioned in Paragraph-9.~~
- ~~The application is divided out of my /our application particulars of which is given in Paragraph-10 and pray that this application may be treated as deemed to have been filed on DD/MM/YYYY under section 16 of the Act.~~
- ~~The said invention is an improvement in or modification of the invention particulars of which are given in Paragraph-11.~~

13. FOLLOWING ARE THE ATTACHMENTS WITH THE APPLICATION

(a) Form 2

Item	Details	Fee	Remarks
Complete/ ~~Provisional~~ specification) #	No. of pages: 22		
No. of Claim(s)	No. of claims: 10 No. of pages: 02		
Abstract	No. of pages: 01		
No. of Drawing(s)	No. of drawings: 14 No. of pages: 04		

In case of a complete specification, if the applicant desires to adopt the drawings filed with his provisional specification as the drawings or part of the drawings for the complete specification under rule 13(4), the number of such pages filed with the provisional specification are required to be mentioned here.

(b) Complete specification (in conformation with the international application)/as amended before the International Preliminary Examination Authority (IPEA), as applicable (2 copies).

(c) Sequence listing in electronic form

(d) Drawings (in conformation with the international application)/as amended before the International Preliminary Examination Authority (IPEA), as applicable (2 copies).

(e) Priority document(s) or a request to retrieve the priority document(s) from DAS (Digital Access Service) if the applicant had already requested the office of first filing to make the priority document(s) available to DAS.

(f) Translation of priority document/Specification/International Search Report/International Preliminary Report on Patentability.

(g) Statement and Undertaking on Form 3

(h) Declaration of Inventorship on Form 5

(i)Power of Authority

(j)**Total fee ₹……….in Cash/ Banker's Cheque /Bank Draft bearing No.......... Date on …………. Bank.**

I/We hereby declare that to the best of my/our knowledge, information and belief the fact and matters slated herein are correct and I/We request that a patent may be granted to me/us for the said invention.

Dated this 02nd day of September 2023

Applicant: Andhra University

To,

The Controller of Patents

The Patent Office, at Chennai

Note: -

* Repeat boxes in case of more than one entry.
* To be signed by the applicant(s) or by authorized registered patent agent otherwise where mentioned.
* Tick ()/cross (x) whichever is applicable/not applicable in declaration in paragraph-12.
* Name of the inventor and applicant should be given in full, family name in the beginning.
* Strike out the portion which is/are not applicable.
* For fee: See First Schedule";

FORM 2

THE PATENTS ACT, 1970

(39 of 1970)

&

The Patent Rules, 2003

COMPLETE SPECIFICATION

(See section 10 and rule 13)

TITLE OF THE INVENTION

“A Novel Deep Learning Technique to Identify Chronic Kidney Disease (CKD) through Effective Feature Selection and Classification”

Applicant

NAME	**NATIONALITY**	**ADDRESS**
Andhra University	Indian	Visakhapatnam, Andhra Pradesh, India. Pin Code: 530003

The following specification particularly describes the nature of the invention and the manner in which it is performed:

FIELD OF THE INVENTION

[001] The invention pertains to the field of the system and method to identify chronic kidney disease, more particularly a novel deep learning technique to identify chronic kidney disease (CKD) through effective feature selection and classification.

BACKGROUND OF THE INVENTION

[002] The following description provides the information that may be useful in understanding the present invention. It is not an admission that any of the information provided herein is prior art or relevant to the presently claimed invention, or that any publication specifically or implicitly referenced is prior art.

[003] The increasing chronic kidney disease (CKD) rate is an essential problem for worldwide public health. High mortality rates are associated with the illness, particularly in poorer nations. Since there are no visible early-stage signs, CKD frequently goes undiagnosed. In the meantime, preventing the disease from progressing requires early detection and early clinical care. However, in earlier research, the performance computation time was longer, and the forecast accuracy was lower. To help clinicians discover CKD early, Deep Learning (DL) models can offer an efficient and affordable computer-aided diagnostic. We provide a unique, deep learning-optimized method to predict CKD to get around the issues. It has five steps to perform. Initially, eliminate the missing values, reduce data noise, and normalize in the pre-processing stage. After that, extract the features using the EfficientNet V2 technique. After extracting features, we must select the necessary features to reduce the classification evaluation time utilizing Binary Dandelion Algorithm

(BDA). Then, predict whether the person has CKD using the Hierarchical Multi-scale Long Short-Term Memory (HMLSTM) technique. We used Lion Swarm Optimization Algorithm (LSOA) to improve the prediction accuracy. We get information for the experiment from the chronic kidney disease dataset. The experimental findings also demonstrate a favorable impact of feature selection on evaluating the different techniques. The proposed technique has developed a reliable classification system for detecting CKD and might be used to identify diseases in more unbalanced medical datasets.

[004] Chronic kidney disease (CKD), a long-term disorder that worsens with time, impacts the kidneys' function. The kidneys are essential organs that filter waste and extra fluid from the blood to create urine. CKD occurs when the kidneys are damaged and unable to filter and eliminate waste products properly. Hypertension, glomerulonephritis, diabetes, polycystic kidney disease, and other kidney-related disorders are only a few of the conditions that can lead to CKD. Glomerulonephritis is an infection of the kidney's filtration units. Age, smoking, obesity, family history of renal disease, and certain drugs are all risk factors for CKD. CKD is divided into phases based on the eGFR, which gauges how well the kidneys are working. The stages vary from Stage 1 (minimally damaged kidneys with normal or high eGFR) to Stage 5 (end-stage renal disease, where patients frequently need dialysis or a kidney transplant because kidney function is substantially compromised). CKDs at the beginning may not be accompanied by any apparent symptoms [6-9]. Fatigue, fluid retention (edema), swelling in the legs and ankles, more frequent nighttime urination, difficulties concentrating, anemia, and high blood pressure are among the symptoms that may emerge as the condition worsens.

If neglected, CKD can result in significant complications such as heart disease, bone problems, anemia, electrolyte imbalances, and, in severe cases, the requirement for dialysis or kidney transplantation. CKD is identified through urine and blood tests that evaluate renal function and damage. Essential markers for identification and prognosis include eGFR and albuminuria (protein in the urine). Treatment of the underlying causes, regulation of blood pressure and blood sugar levels, control of fluid and electrolyte balance, and dietary and lifestyle changes are all necessary for CKD management. Medications may be recommended to control side effects and prevent the condition from worsening. A balanced diet, moderate exercise, addressing underlying medical disorders, limiting alcohol intake, quitting smoking, and testing kidney function frequently are examples of preventive approaches.

[005] All the necessary medical information and health factors can be analyzed using ML techniques in forecasting systems. This is an efficient method for making early medical diagnoses to accurately and effectively examine the patient's health. Data mining techniques, such as categorization methods, are potent tools frequently employed in numerous research as an efficient disease forecasting and anomaly detection strategy. Offline gathering, processing, and analyzing data are still limitations in most CKD prediction systems. Using too many characteristics could lengthen the process's execution and reduce its accuracy in predicting CKD. However, in recent research, various clinical symptoms like chest discomfort, nausea, insomnia, and other indications that might greatly aid in the early detection of potential CKD have been disregarded in addition to those criteria. These problems drive us to develop a diagnostic forecasting system for CKD using attribute-chosen algorithms among all potential influencing elements to address the abovementioned constraints. The critical contribution of this paper is,

• In the pre-processing stage, eliminate the missing values, reduce noise from the data, and normalize the data.

• To extract the features using the EfficientNet V2 technique. After extracting features, we must select the necessary features to reduce the classification evaluation time utilizing Binary Dandelion Algorithm (BDA).

• Then, predict whether the person they have CKD or not using the HMLSTM technique. We used Lion Swarm Optimization Algorithm (LSOA) to improve the prediction accuracy.

• The evaluation of this research is performed on the chronic kidney disease dataset. And also with accuracy, precision, sensitivity, specificity, and AUC metrics.

[006] Accordingly, on the basis of aforesaid facts, there remains a need in the prior art to provide development of a novel deep learning technique to identify chronic kidney disease (CKD) through effective feature selection and classification. Therefore, it would be useful and desirable to have a system, method, apparatus and interface to meet the above-mentioned needs.

SUMMARY OF THE PRESENT INVENTION

[007] The present invention relates to a novel deep learning technique to identify chronic kidney disease (CKD) through effective feature selection and classification.

[008] In one aspect of the present invention, chronic kidney disease (CKD) is a progressive and long-term condition where the kidneys gradually lose their function over time. Early detection and proactive management are crucial in slowing the progression of CKD and improving quality of life. To predict CKD, we propose a novel deep-learning technique. There are five steps to achieving it. First, in the pre-processing stage, remove missing values and normalize the data while reducing noise. Then, employ the EfficientNet V2 approach to extract the features. The Binary Dandelion Algorithm (BDA) must be used to choose the necessary features once features have been extracted to speed up classification evaluation. Then, using the HMLSTM approach, determine whether the person has CKD. We employed the Lion Swarm Optimization Algorithm (LSOA) to increase forecast accuracy. The dataset on chronic renal illness provides the data we need for the experiment. Figure 1 shows the architecture of the proposed method.

[009] In this respect, before explaining at least one object of the invention in detail, it is to be understood that the invention is not limited in its application to the details of set of rules and to the arrangements of the various models set forth in the following description or illustrated in the drawings. The invention is capable of other objects and of being practiced and carried out in various ways, according to the need of that industry. Also, it is to be understood that the phraseology and terminology employed herein are for the purpose of description and should not be regarded as limiting.

[010] These together with other objects of the invention, along with the various features of novelty which characterize the invention, are pointed out with particularity in the disclosure. For a better understanding of the invention, its operating advantages and the specific objects attained by its uses, reference should be made to the accompanying drawings and descriptive matter in which there are illustrated preferred embodiments of the invention.

BRIEF DESCRIPTION OF THE DRAWINGS

The invention will be better understood and objects other than those set forth above will become apparent when consideration is given to the following detailed description thereof. Such description makes reference to the annexed drawings wherein:

Figures 1-14 illustrate various representation of a novel deep learning technique to identify chronic kidney disease (CKD) through effective feature selection and classification, in accordance with an embodiment of the present invention.

DETAILED DESCRIPTION OF THE INVENTION

[011] While the present invention is described herein by way of example using embodiments and illustrative drawings, those skilled in the art will recognize that the invention is not limited to the embodiments of drawing or drawings described and are not intended to represent the scale of the various components. Further, some components that may form a part of the invention may not be illustrated in certain figures, for ease of illustration, and such omissions do not limit the embodiments outlined in any way. It should be understood that the drawings and detailed description thereto are not intended to limit the invention to the particular form disclosed, but on the contrary, the invention is to cover all modifications, equivalents, and alternatives falling within the scope of the present invention as defined by the appended claims.

As used throughout this description, the word "may" is used in a permissive sense (i.e. meaning having the potential to), rather than the mandatory sense, (i.e. meaning must). Further, the words "a" or "an" mean "at least one" and the word "plurality" means "one or more" unless otherwise mentioned. Furthermore, the terminology and phraseology used herein is solely used for descriptive purposes and should not be construed as limiting in scope. Language such as "including," "comprising," "having," "containing," or "involving," and variations thereof, is intended to be broad and encompass the subject matter listed thereafter, equivalents, and additional subject matter not recited, and is not intended to exclude other additives, components, integers or steps. Likewise, the term "comprising" is considered synonymous with the terms "including" or "containing" for applicable legal purposes. Any discussion of documents, acts, materials, devices, articles and the like is included in the specification solely for the purpose of providing a context for the present invention. It is not suggested or represented that any or all of these matters form part of the prior art base or were common general knowledge in the field relevant to the present invention.

[012] In this disclosure, whenever a composition or an element or a group of elements is preceded with the transitional phrase "comprising", it is understood that we also contemplate the same composition, element or group of elements with transitional phrases "consisting of", "consisting", "selected from the group of consisting of, "including", or "is" preceding the recitation of the composition, element or group of elements and vice versa.

[013] The present invention is described hereinafter by various embodiments with reference to the accompanying drawings, wherein reference numerals used in the accompanying drawing correspond to the like elements throughout the description. This invention may, however, be embodied in many different forms and should not be construed as limited to the embodiment set forth herein. Rather, the embodiment is provided so that this disclosure will be thorough and complete and will fully convey the scope of the invention to those skilled in the art. In the following detailed description, numeric values and ranges are provided for various aspects of the implementations described. These values and ranges are to be treated as examples only and are not intended to limit the scope of the claims. In addition, a number of materials are identified as suitable for various facets of the implementations. These materials are to be treated as exemplary and are not intended to limit the scope of the invention.

[014] The present invention discloses a novel deep learning technique to identify chronic kidney disease (CKD) through effective feature selection and classification.

[015] The present invention gathers the data from the dataset in this step. The input data are removing the missing values and reduce the noise in data. Then normalize the data using min-max normalization method. Both min-max normalization and z-score-based normalization are implemented at the normalization stage. Normalization is a helpful technique for adjusting the stock information to fit within a specific range when employing many historical stock data. After normalization, gradient descent quickens and gets more precise [21]. Min-Max normalization is widely used to scale the data between specified ranges by applying a linear trend to the starting date. The notations $x_{\min}$ $x_{\max}$ stand for an attribute's lowest and most significant values. The value x is computed to a value in the range [$x_{\min}$ and $\max_x$] to calculate the distinction between the two values. The normalized data for the CKD dataset is shown in Figure 2:

$$z_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}}\left(New_{\max_x} - New_{\min_x}\right) + New_{\min_x} \tag{1}$$

where the variables $x_{\min}$ $x_{\max}$ stand in for the lowest and highest values, respectively. The notation $New_{\min_x}$ represents the smallest integer, whereas it $New_{\max_x}$ represents the largest.

Feature Extraction

EfficientNetV2 is used in this system to extract significant attributes from the input data. A new family of convolutional neural networks called EfficientNetV2 is an upgraded version of EfficientNetV1, emphasizing two specific areas: increasing training time and increasing parameter efficiency. Compound scaling and training-aware search for neural architecture were combined for this purpose. The Fused-MBConv are the core building blocks of EfficientNetV2.

There are seven blocks in the EfficientNetV2 networks. All blocks in EfficientNetV1 are MBConv. Fused-MBConv is used in the first three blocks instead of MBConv to increase training speed and decrease model complexity [22]. Three additional blocks are made up of MBConv blocks. Block 7 comprises a complete connection layer, an average pooling layer, and a 1x1 convolution layer. A 1x1 ordinary convolution, a 1x1 ordinary convolution, a SE module, a kxk depth-wise convolution, and a dropout layer comprise most of the MBconv structure. Equations (2) and (3) show the convolutional layer equations

$$z^l = a^{l-1} * W^l + b^l \tag{2}$$

$$a^l = f^l(z^l) \tag{3}$$

The SE module comprises two completely connected layers plus a global average pool. To improve feature representations, the SE block uses an attention technique. ReLU discards value less than zero, which could lead to the loss of crucial information. Therefore, the network utilizes the h-swish value as an activation function instead. The following describes the h-Swish:

$$h - swish(x) = x.\sigma(x) \quad (4)$$

$$.\sigma(x) = \frac{\mathrm{Re}\,LU6(x+3)}{6} \quad (5)$$

Here, σ(x) is the piece-wise linear complex analog function.

The fused-MBconv block is another significant node in this network. The primary branch of the initial MBConv structure's expansion Conv1x1 and depth-wise convolutions 3x3 are swapped out for a conventional conv3x3. The input data undergoes transformations and convolutions as it moves through the network's layers and blocks. Feature maps, which are illustrations of the input information at various levels of abstraction, are the end product of these processes.

Feature Selection

The feature selection procedure is required to reduce the evaluation period in research. The evaluation process can be improved by removing the extraneous characteristics and choosing the essential features. In this case, the Binary Dandelion Algorithm (BDA) was used to choose the required characteristics. Previous research has demonstrated that DA performs better than some other conventional intelligent optimization algorithms [23]. When optimization precision and speed of convergence are assessed on some benchmark functions, DA performs best. Since DA performs so well, it is thought to be used to attribute chosen. However, because the components of the search space are Boolean values rather than continuous DA values, feature selection cannot be done so. As a result, BDA is altered and recommended to utilize the original method.

The search area used for feature selection is binarized, meaning that it only comprises the digits 0 and 1. where 1 denotes the selection of the feature within the same dimension, and 0 denotes the non-selection of the attribute within the same dimension. Like DA, BDA is broken down into initialization, variant seeding, standard seeding, and selection strategy components. To utilize DA for creating feature subsets, one must first discretize the search space because it operates in a continuous space.

Normal sowing

The transfer function is a fairly straightforward, effective, and popular approach for converting continuous optimization to binary optimization, among many others. The standard seeding method uses a transfer function to convert the seeding ratio into the likelihood that the location vector components will take the value 0 or 1.

Position formula

The location vector elements in the binary optimization technique can only have values of 0 or 1. The value of the location vector's components can be immediately determined by probability to be either 0 or 1. This method is popular since it is easy to understand and uncomplicated. As indicated in Eq. (6), a different approach is taken to determine the values of the vector's position components by chance that they will be the same as the previous generation or will be taken inversely.

$$X_{i.j}^{i+1} = \begin{cases} x_{i.j}^{t} & p_{i.j}^{t} < rand() \\ 1 - X_{i.j}^{t} & p_{i.j}^{t} \geq rand() \end{cases} \qquad (6)$$

Mutation seeding

The initial variationally seeding formula is no longer relevant because the search area and the location vector are converted into binary form. The vector's position components are a bit inverted to have a similar impact on enhancing the candidate answers, as stated in Eq. (7). This approach is rapid and effective, and by using dandelions to create complimentary solutions, it enables a more thorough search of the answer space in the iterative phase.

$$X_{mi.j} = -X_{i.j} \qquad (7)$$

Evaluation function

The categorization error rate of the set of tests in the classifier is frequently the most crucial benchmark to be assessed in feature selection. The number of characteristics chosen should also be taken into account in addition to this. Less redundancy and fewer features generally make the following stage of feature processing easier. As a result, as indicated in Eq. (8), the success rate of the attribute set and the amount of chosen attributes must be combined in the evaluation function:

$$Fitness(X) = \rho \times (1 - Error(X)) + (1 - \rho) \times \frac{|F|}{|N|} \quad (8)$$

Seeding radius

A crucial component of the algorithm is the change in the sowing radius. The measure of the sowing radius directly impacts where the seeds land. Because each position vector element must be operated on, the seeding range of every seed is altered. The initial seeding radius calculation for the core dandelion would have produced the identical seeding radius for every dimension, which prevents differential tuning of each dimension. Eq. (8) is therefore suggested to accomplish the objective. The assistant dandelion's seeding radius also receives some adjustments. Eq. (9) calculates the seeding radius of every dimension by contrasting the core dandelion with every assistant dandelion.

$$R_{CDi.j}^{\;t} = \begin{cases} Bound \quad t = 1 \\ R_{CDi.j}^{\;t-1} * r + r1 \; a = 1 \\ R_{CDi.j}^{\;t-1} * e + r2 \; a \neq 1 \end{cases} \quad (9)$$

Bound is the largest seeding radius, e, r is the growth factor and wilting factor from Eq. (9), an is the judgment factor, and r1, r2 are two random values between [0.5, 0.5].

$$R_{AD_{i.j}^{t}} = \begin{cases} Bound & t = 1 \\ w \times R_{AD_{i.j}^{t-1}} + r3 \times (r4 \times X_{CD_{i.j}^{t}} - X_{AD_{i.j}^{t}}) & t > 1 \end{cases} \quad (10)$$

Where w is the Eq. (10) weighting factor and r3, r4 are two random values between [0, 1], respectively.

Classification/Prediction

Finally, we utilize the Hierarchical Multi-scale Long Short-Term Memory technique to categorize the speech's emotions into CKD. A modified LSTM called HMLSTM is used in this work for this purpose. HMLSTM comes in a variety of forms. The HMLSTM has been modified in this study to meet the needs of the IDS model. The general LSTM uses three gates to obtain inputs, which are then processed using the sigmoid activation method [24]. This HMLSTM introduces a parameterized boundary detector that generates binary output values for each layer to learn the termination conditions and produce the temporal attributes. Also included are the dense connections, which enable layer l to take as input the attribute maps from all preceding layers and generate a concatenation of attribute maps. The LSTM model's spatial attribute learning property is improved through this method, which also increases the classifier's effectiveness for intrusion detection. The standard LSTM equations are created first.

$$Gates\,and\,candidate: \begin{bmatrix} i_t \\ f_t \\ u_t \\ o_t \end{bmatrix} = Wx_t + Uh_{t-1} + b \tag{11}$$

$$Cell\ state: c_t = c_{t-1} \Theta \sigma(f_t) + \tanh(u_t) \Theta \sigma(i_t) \tag{12}$$

$$Hidden\ state: h_t = \sigma(o_t) \Theta \tanh(c_t) \tag{13}$$

Here, it stands for the LSTM's current input, ht1 for the previous hidden state, and ct1 for the prior cell state. The LSTM receives these three parameters as input. The letters it, ft, ut, and out denote the forget, input, output gates, and candidate activation. The weight matrix is represented by W, the activation function matrix by U, and the bias is represented by b.

When these standard functions are combined with the boundary detector variable (zt),

$$\begin{bmatrix} i_t \\ f_t \\ u_t \\ o_t \\ z_t \end{bmatrix} = Wx_t + Uh_{t-1}^{1} + z_{t-1}Vh_{t-1}^{2} + b \qquad (14)$$

The update process is carried out at each layer in the proposed HMLSTM system, which has L layers (ℓ = 1, 2, . . . , L) at time t.

$$h_t^l, c_t^l, z_t^l = f_{HMLSTM}^{l}\left(c_{t-1}^{l}, h_{t-1}^{l}, h_t^{l-1}, h_{t-1}^{l+1}, z_{t-1}^{l}, z_t^{l-1}\right) \qquad (15)$$

The forget gate of HMLSTM, obtained by the two border states ztℓ−1, ztℓ−1 is represented by the function fHMLSTM ℓ. The statuses of the cells can be updated as

$$c_t^l = \begin{cases} f_t^l \Theta c_{t-1}^l + i_t^l \Theta g_t^l & if\ z_{t-1}^l = 0 \quad and \quad z_t^{l-1} = 1 (Update) \\ c_{t-1}^l & if\ z_{t-1}^l = 0 \quad and \quad z_t^{l-1} = 0 (Copy) \\ i_t^l \Theta g_t^l & if\ z_{t-1}^l = 1 (Flush) \end{cases} \qquad (16)$$

Suppose the boundary ztℓ−1 is discovered at the bottom layer, but ztℓ−1 was absent in the previous time step. In that case, the Update operation is carried out to update the summary representation of the layer ℓ. Update operations are only occasionally used because this circumstance happens so infrequently. The copy procedure is as simple as (h1 t, ct1) ← (h1 t−1, ct1−1). This means that the top layer remains unmodified until the bottom layer's summarized input is received. This indicates that Reset deletes the bottom layer summary if eject is not run but permits the upper layer to absorb it otherwise.

The slice function can determine the gate values (ftℓ, iℓ t, oℓ t), cell proposal (gtℓ), and preactivation of the boundary detector (z˜tℓ = rigid sign (Uhℓ t)) for each operation.

$$\begin{bmatrix} f_t^l \\ i_t^l \\ o_t^l \\ g_t^l \\ \tilde{z}_t^l \end{bmatrix} = \begin{bmatrix} sigm \\ sigm \\ sigm \\ \tanh \\ hardsigm \end{bmatrix} f_{slice}(s_t^{recuurent(l)} + s_t^{top-down(l)} + s_t^{bottom-up(l)} + b)$$

(17)

Here

$$s_t^{recuurent(l)} = U_l^l h_{t-1}^l \qquad (18)$$

$$s_t^{top-down(l)} = z_{t-1}^l U_{l+1}^l h_{t-1}^{l+1} \qquad (19)$$

$$s_t^{bottom-up(l)} = z_t^{l-1} W_{l-1}^{ll-1} ht \qquad (20)$$

It is determined that the binary boundary state ztℓ is

$$z_t^l = f_{bound}(\tilde{z}_t^l) \qquad (21)$$

The deterministic step function can be used to model it.

$$z_t^l = \begin{cases} 1 & if\ \tilde{z}_t^l > 0.5 \\ 0 & otherwise \end{cases} \qquad (22)$$

Using HMLSTM technique, we achieved higher classification accuracy. But, to improve the classification accuracy, utilizing Lion Swarm Optimization (LSO) algorithm.

Optimization

[016] The Lion Swarm Optimization (LSO) is a new player in meta-heuristic algorithms. It is based on the natural division of labor between the lionesses, lion king, and lion cubs in a lion group, with the lion king defending and lion cubs and lionesses hunting following. Due to benefits including its straightforward structure, limited number of control parameters, ease of execution, good resilience, and quick iteration speed, LSO has been extensively employed to address various real-world optimization issues. Several LSO variations have also been developed.

The behavior of real lions

In contrast to other species of the Felidae family, lions typically form two social groups: resident lions, which typically number fifteen or more on average. Apex predators are those at the top of a food chain, and lions are considered to be these predators. The lion group has an apparent social dominance order.

Lion King: According to the principle of survival of the fittest. This dominant male can breed with almost all females in the pride to produce progeny. In addition to protecting the lion cubs and providing accommodation for the cubs, the lion king must keep their territory free from invasion from both within and without the groupings. Additionally, the lion king must be powerful enough to repel the threat; otherwise, other male lions from the group or outside it will take over as king. If the other male lions defeat the lion king, they may be murdered or driven from pride and become wandering lions. The newly anointed lion king has the power to drive lionesses into estrus and cohabitate with their young. It will also try to murder the lion cubs produced by its forebears.

Lionesses: The primary duties of the lionesses, commonly referred to as the stalking lions, include raising the lion pups and stalking in concert with the prey trail. The lionesses follow the prey's track over a vast area, and as they get close to the prey, they can see where the prey is and encircle them.

Lion cubs mostly conduct their activities around the mother lioness and the lion king. The typical behavior of lion cubs can be broken down into three categories: (1) approaching the lion king for food; (2) following the lioness to learn how to hunt; and (3) when they gain maturity and go out of the group and become nomadic lions. To work together, every lion needs to be more complex. But when grouped, they can work as a team to find food while adhering to a precise social hierarchy. Three populations in LSO have various location updating policies.

LSO algorithm

The explanations above allow us to create LSO mathematically [25]. First, we provide the LSO principle: The program uses a bottom-up design approach inspired by lion swarm hunting behavior and based on a notion of autonomous animates. The lion king will take control of the location of the prey once it is discovered and is superior to the prey it currently occupies.

Definition of parameters

(1) The proportion factor of adult lions β

The percentage of big lions in the lion team significantly affects the optimization outcome. The proportion of big lions increases as the amount of lion cubs decreases. The adult lion percentage factor β is a positive random amount between [0,1]. Here, we set β to be smaller than 0.5 to ensure the quick convergence of the LSO.

(2) The moving range disturbance factor of lionesses αf

An optimizer's global exploration capability is crucial for issues that are challenging to optimize. The local exploration capability needs to be strengthened after the approximate location of the ideal solution has been determined. The lionesses' range of activity will gradually shrink as the updating process continues. The following is a definition of the phrase for the disturbance factor f:

$$a_f = Step_1.\exp\left(-30.\frac{t}{T}\right)^{10} \tag{23}$$

Where T is the number of iterations that can be made, t is the current iteration's tth, and Step1 indicates the value of the step in the lionesses' activity range, which is determined by

$$Step_1 = a_1.\left(\overline{x_{\max}} - \overline{x_{\min}}\right) \tag{24}$$

Where max x and min x represent the minimal and maximum means of each dimension, the lioness' step is known to be controlled by a1 and a randomized number in the [0, 1] range.

Random initialization

Every lion location in the LSO algorithm indicates a potential answer to the issue under consideration, and the caliber of the prey reflects the caliber (fitness) of the corresponding answer.

$$x = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & \cdots & x_{2,D} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & \cdots & x_{n,D} \end{bmatrix}$$

(25)

Fitness evaluation

By feeding the values of the choice variable into user-defined fitness functions, the fitness value of location for every lion is determined, and the related fitness values can be written as follows:

$$\begin{bmatrix} f_1([x_{1,1}, x_{1,2}, \cdots, x_{1,D}]) \\ f_2([x_{2,1}, x_{2,2}, \cdots, x_{2,D}]) \\ \vdots \\ \vdots \\ f_n([x_{n,1}, x_{n,2}, \cdots, x_{n,D}]) \end{bmatrix}$$

(26)

Hunting Behaviors of Lions

[017] Every lion in LSO updates its location based on its self-experience and its neighbors' experiences. As was already noted, distinct lions move in various hunting postures during the hunting process. The following brief list of benefits can be used to summarize the proposed hunting mechanism.

[018] ***The lion king:*** The lion king may move to the area with the finest food, i.e., the location with the lowest fitness value, to ensure that he has priority over the other lions hunting prey. In this instance, the following steps might be taken to earn the new title of lion king:

$$x_i(t+1) = gbest(t).(1+\gamma.\|pbest_i(t) - gbest(t)\|)$$

(27)

Lionesses: The typical hunting strategy involves spotting their target, surrounding them, and then charging at them. When lionesses engage in hunting behavior, they frequently work together. Remember that the lioness chosen from the lioness group to cooperate is someone other than herself. The new status of the lionesses in this situation is as follows:

$$x_i(t+1) = \frac{pbest_i(t) + pbest_c(t)}{2}.\left(1 + a_f.\gamma\right)$$

(28)

Lion cubs: Three scenarios may arise while lion cubs are actively hunting, as was stated above. In this situation, the lion cubs' new location can be obtained as follows:

$$x_i(t+1) = \begin{cases} \frac{gbest(t) + pbest_i(t)}{2}.\left(1 + a_c.\gamma\right), \ q \le \frac{1}{3} \\ \frac{pbest_m(t) + pbest_i(t)}{2}.\left(1 + a_c.\gamma\right), \ \frac{1}{3} < q < \frac{2}{3} \\ \frac{\overline{gbest(t)} + pbest_i(t)}{2}.\left(1 + a_c.\gamma\right), \ \frac{2}{3} \le q \le 1 \end{cases}$$

(29)

Results and Discussion

[019] The system's development findings are presented in this section. The settings for hyper-parameters shown Table 1.

Table 1. Settings for hyper-parameters.

Hyper-Parameter	Setting
Batch size	15
Epochs	850
Activation Function	Relu
Optimizer	Adam
Dropout rate	0.5 to 0.1

Loss	Binary_Crossentropy
Activation output layer	Sigmoid

Experimental Setup

[020] Different environments have been used in the system's development. The environment configuration for the evolving system is displayed in Table 2.

Table 2. Environment setup of the proposed system.

Resource	Details
CPU	Core i5 Gen6
RAM	8 GB
GPU	4GB
Software	Python

Dataset Description

[021] The CKD dataset contains 400 patients. In addition to the class features, such as "CKD" and "notckd" for classification, the dataset has 24 features, separated into 11 numerical and 13 categorical features. The following characteristics are present: specific gravity, albumin, blood pressure, red blood cells, pus cell, bacteria, sugar, serum creatinine, blood urea, sodium, hemoglobin, potassium, diabetes mellitus, red blood cell count, packed cell volume, white blood cell count, appetite, hypertension, pedal edema, coronary artery disease, and anemia. Notckd and CKD are the two values in the diagnostic class.

Table 3. Splitting Dataset.

Dataset	Numbers
Training	320 patients

Testing and validation	80 patients

The dataset was split into 20% for testing and validation and 80% for training. The split data are displayed in Table 3.

Evaluation Metrics

Performance indicators were employed to assess each of the four classifiers' capabilities. One of these metrics is the confusion matrix, from which the accuracy, sensitivity, specificity, and AUC are derived by computing the properly categorized samples and the wrongly classified samples as illustrated in the following equations:

Accuracy

It measures the proportion of accurate forecasts to all other forecasts. Accuracy can be defined as the ability to forecast outcomes with accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (30)$$

Sensitivity

This shows the capacity to identify a patient at risk for heart disease and is assessed as stated in equation (30).

$$Sensitivity = \frac{a_p}{a_p + b_n} \quad (31)$$

Specificity

This can be calculated by dividing the total number of negatives by the true negatives, as shown in (32). Value 1.0 designates the best specificity, while 0.0 designates the poorest. $Specificity = \frac{a_n}{a_n + b_p}$

(32)

The area under the ROC curve (AUC)

AUC is the variation between the ROC curve's area above and below. AUC, which reduces the ROC curve outcome into a scalar value and is computed as shown in equation (48), is a measure of accuracy.

$$AUC = \int_x^y f(v)dv \tag{33}$$

Evaluation of Proposed Implementation

[022] In this paper, we propose a new technique to predict CKD. Here, we show results as GUI for whether the person has CKD or not. In Figure 3, we display the actual front page for inputting patient information. Python Tkinter generates this GUI.

Figure 4 shows that if all the patient information is usual, it will show as "Great! You don't have a chronic kidney disease".

Figure 5 shows that if all the patient information is usual, it will show as "Oops! You have a chronic kidney disease".

Performance of classification techniques without feature selection

[023] The experimental findings from classifier training using the entire feature set are shown in this subsection. Table 4 presents these findings. Additionally, Figure 6 displays each classifier's ROC curves and AUC values.

Figure 7. Accuracy, Sensitivity, and Specificity for each classifier without feature selection.

[024] The proposed Optimized EfficientNetV2 outperformed other classifiers to perform well without feature selection shown in Figure 7.

Performance of classification techniques with feature selection

[025] The qualities of chronic kidney disease were ranked using information gained as a basis for feature selection. This stage aims to choose the features that will provide the most information about the target variable. The proposed

Optimized EfficientNetV2 and the other classification techniques are trained using the minor attribute set to show the value of attribute selection. In Table 5, the experimental findings are displayed. Figure 8 also displays the ROC curve as well as various AUC values. The evaluation outcomes in Table 5 and Figure 8 demonstrate that the proposed Optimized EfficientNetV2 outperformed the Decision Tree, Logistic Regression, Random Forest, XGBoost, AdaBoost, and SVM. This improvement demonstrates the success of the feature selection stage. As a result, a powerful strategy for predicting CKD uses feature selection in conjunction with Optimized EfficientNetV2.

Figure 9. Accuracy, Sensitivity, and Specificity for each classifier after feature selection. The proposed Optimized EfficientNetV2 outperformed other classifiers to perform well without feature selection shown in Figure 9.

Correlation Matrix

[026] A correlation matrix is often used in statistics and data analysis to understand relationships between multiple variables. Each cell in the matrix represents the correlation coefficient between two variables. If the data contains n variables, the correlation matrix will be an n x n matrix. Correlation matrices are often visualized using heatmaps, which use color gradients to represent the strength of correlations. This visualization can help identify patterns and relationships within the data.

Figure 10 shows the correlation matrix between different features.

Comparison

[027] Here, we proposed a technique for predicting CKD. Table 6 shows the overall comparison of proposed and existing methods. Compared to other techniques, the proposed method achieved 99.92% accuracy compared with 97% of DT, 97.8% of LR+NN, 98.5% of DBN, and 97.5% of HMANN.

Figure 11 shows the overall comparison of the proposed with existing methods.

[028] A confusion matrix is a tool used in machine learning and statistics to visualize and assess the performance of a classification model. It summarizes the predictions made by a model on a classification problem, comparing these predictions with the actual accurate data labels. The confusion matrix is beneficial when evaluating the performance of algorithms for tasks like binary or multi-class classification. Figure 12 shows the confusion matrix with and without optimization techniques.

Evaluation of training and testing

[029] Figure 13 displays a loss value and categorization accuracy graph as the number of iteration steps increased. The graph shows how the approach covered in this study benefits convergence.

Computation Time

[030] Performance indicators for the chosen classifier include its error and computing time. Precision, recall, and categorization accuracy will all be taken into account. The computing time is taken into account by each classifier. With low computation time, the proposed Optimized EfficientNet V2 technique. The computation time of the proposed Optimized EfficientNet V2 system is displayed in Figure 14. The computation time for the proposed methodology and existing methodologies.

[031] The computation time using the proposed framework and the most recent methods is shown in Figure 14. Our proposed method outperformed earlier approaches regarding prediction accuracy and computing time.

Conclusion

[032] In this research, we propose a technique to predict chronic kidney disease. There are five steps to achieving it. First, in the pre-processing stage, remove missing values and normalize the data while reducing noise. Then, employ the EfficientNet V2 approach to extract the features. The Binary Dandelion Algorithm (BDA) must be used to choose the necessary features once features have been extracted to speed up classification evaluation. Then, using the HMLSTM approach, determine whether the person has CKD. We employed the Lion Swarm Optimization Algorithm (LSOA) to increase forecast accuracy. The dataset on chronic renal illness provides the data we need for the experiment. The evaluation performance of the proposed method achieved 99.92% accuracy with less computation time compared to other existing techniques. The proposed method overcome the previous literature issues using feature selection technique and optimization algorithm. In the future, we will develop a hybrid technique with an optimization algorithm to increase the accuracy of disease identification before the condition reveals itself in humans.

[033] It is to be understood that the above description is intended to be illustrative, and not restrictive. For example, the above-discussed embodiments may be used in combination with each other. Many other embodiments will be apparent to those of skill in the art upon reviewing the above description.

[034] The benefits and advantages which may be provided by the present invention have been described above with regard to specific embodiments. These benefits and advantages, and any elements or limitations that may cause them to occur or to become more pronounced are not to be construed as critical, required, or essential features of any or all of the embodiments.

[035] While the present invention has been described with reference to particular embodiments, it should be understood that the embodiments are illustrative and that the scope of the invention is not limited to these embodiments. Many variations, modifications, additions and improvements to the embodiments described above are possible. It is contemplated that these variations, modifications, additions and improvements fall within the scope of the invention.

We Claim:

1. A method for predicting Chronic Kidney Disease (CKD) using a deep-learning technique, the method comprising:

   pre-processing data to remove missing values, normalize said data, and reduce noise;

   extracting features from the normalized data using the EfficientNet V2 approach;

   selecting essential features from the extracted features using the Binary Dandelion Algorithm (BDA);

   determining the presence of CKD in a subject using the HMLSTM approach based on the selected features; and

   optimizing prediction accuracy using the Lion Swarm Optimization Algorithm (LSOA).

2. The method as claimed in claim 1, wherein said pre-processing further comprises reducing noise in the data.

3. The method as claimed in claim 1, wherein the features extracted using the EfficientNet V2 approach provide detailed characteristics of potential CKD indicators.

4. The method as claimed in claim 1, wherein the Binary Dandelion Algorithm (BDA) enhances the speed of classification evaluation by selecting only necessary features.

5. The method as claimed in claim 1, wherein the HMLSTM approach is employed to distinguish between subjects with CKD and those without CKD based on the selected features.

6. The method as claimed in claim 1, wherein the Lion Swarm Optimization Algorithm (LSOA) refines the deep-learning model parameters to improve prediction accuracy.

7. A system for predicting Chronic Kidney Disease (CKD), comprising:

a data processor configured to pre-process data by removing missing values, normalizing said data, and reducing noise;

a feature extractor configured to use the EfficientNet V2 approach to extract features from the pre-processed data;

a feature selector employing the Binary Dandelion Algorithm (BDA) to choose necessary features from the extracted features;

a classifier utilizing the HMLSTM approach to determine the presence of CKD based on the selected features; and

an optimizer utilizing the Lion Swarm Optimization Algorithm (LSOA) to enhance the prediction accuracy of the classifier.

8. The system as claimed in claim 7, wherein the data processor further reduces noise in the data for more accurate feature extraction.

9. The system as claimed in claim 7, wherein the feature extractor, using the EfficientNet V2 approach, details potential CKD indicators for improved classification.

10. The system as claimed in claim 7, wherein the optimizer refines the parameters of the deep-learning model for enhanced prediction reliability.

Dated this 02nd day of September 2023

Applicant

Andhra University

ABSTRACT

A Novel Deep Learning Technique to Identify Chronic Kidney Disease (CKD) through Effective Feature Selection and Classification

[036] The present invention relates to a novel deep learning technique to identify chronic kidney disease (CKD) through effective feature selection and classification. The invention introduces a technique to predict chronic kidney disease. There are five steps to achieving it. First, in the pre-processing stage, remove missing values and normalize the data while reducing noise. Then, employ the EfficientNet V2 approach to extract the features. The Binary Dandelion Algorithm (BDA) must be used to choose the necessary features once features have been extracted to speed up classification evaluation. Then, using the HMLSTM approach, determine whether the person has CKD. We employed the Lion Swarm Optimization Algorithm (LSOA) to increase forecast accuracy. The dataset on chronic renal illness provides the data we need for the experiment. The evaluation performance of the proposed method achieved 99.92% accuracy with less computation time compared to other existing techniques. The proposed method overcome the previous literature issues using feature selection technique and optimization algorithm. In the future, we will develop a hybrid technique with an optimization algorithm to increase the accuracy of disease identification before the condition reveals itself in humans.

Dated this 02nd day of September 2023

Applicant

Andhra University

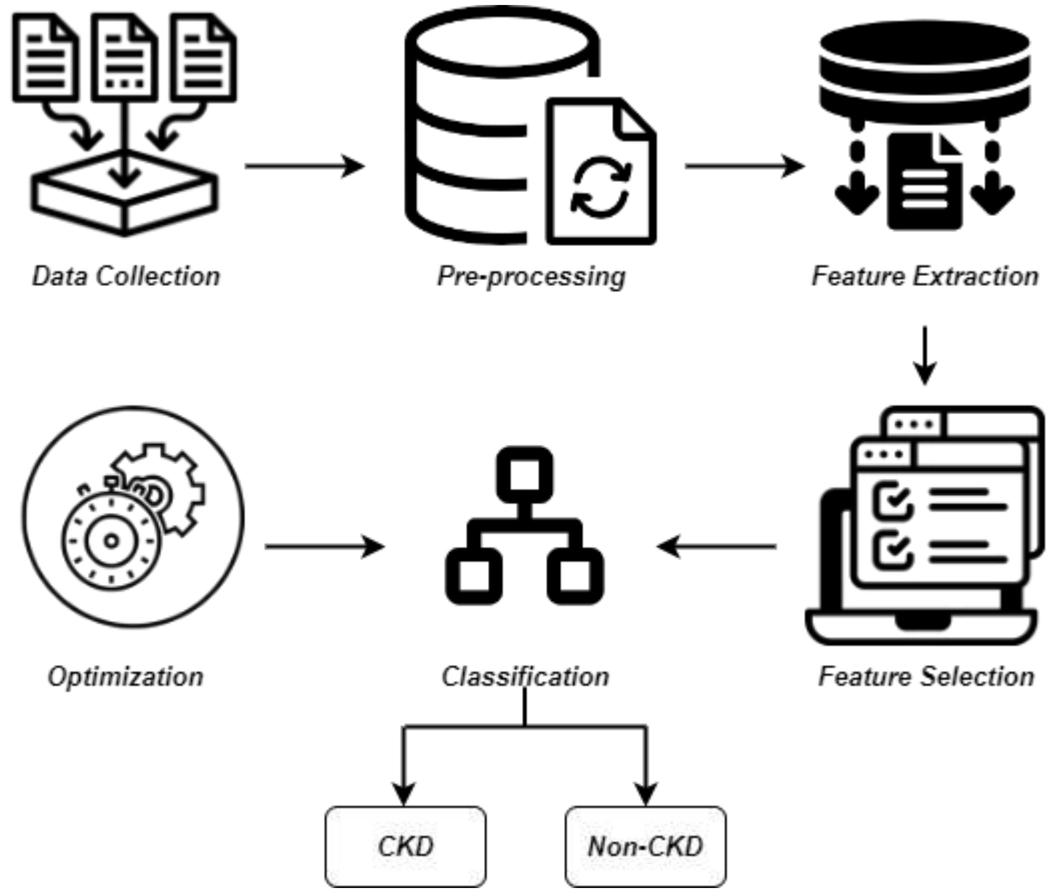
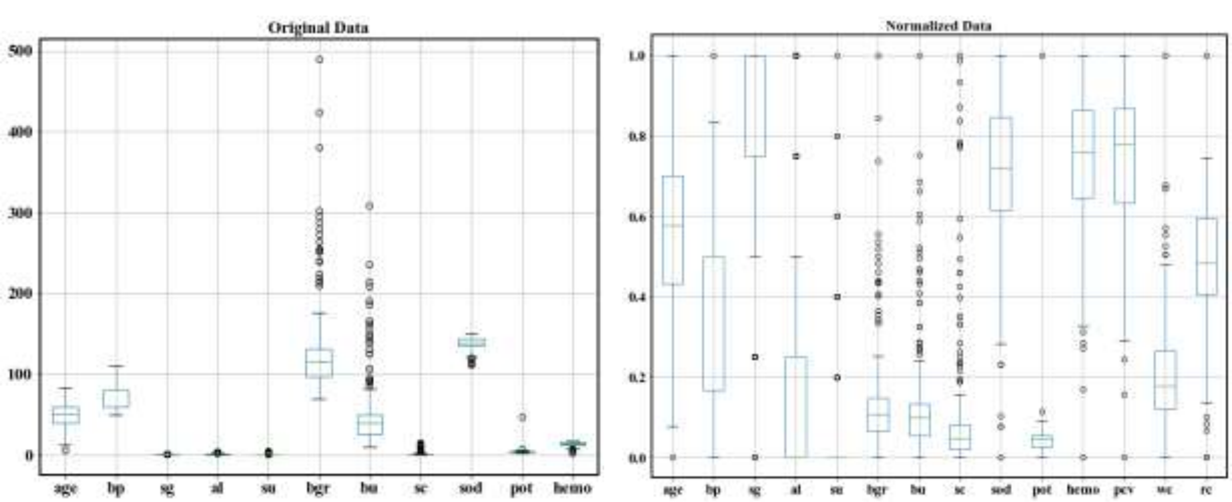


Figure 1. The architecture of the proposed methodology.



(a) (b)

Figure 2. The normalization of (a) Original data, (b) Normalized data.

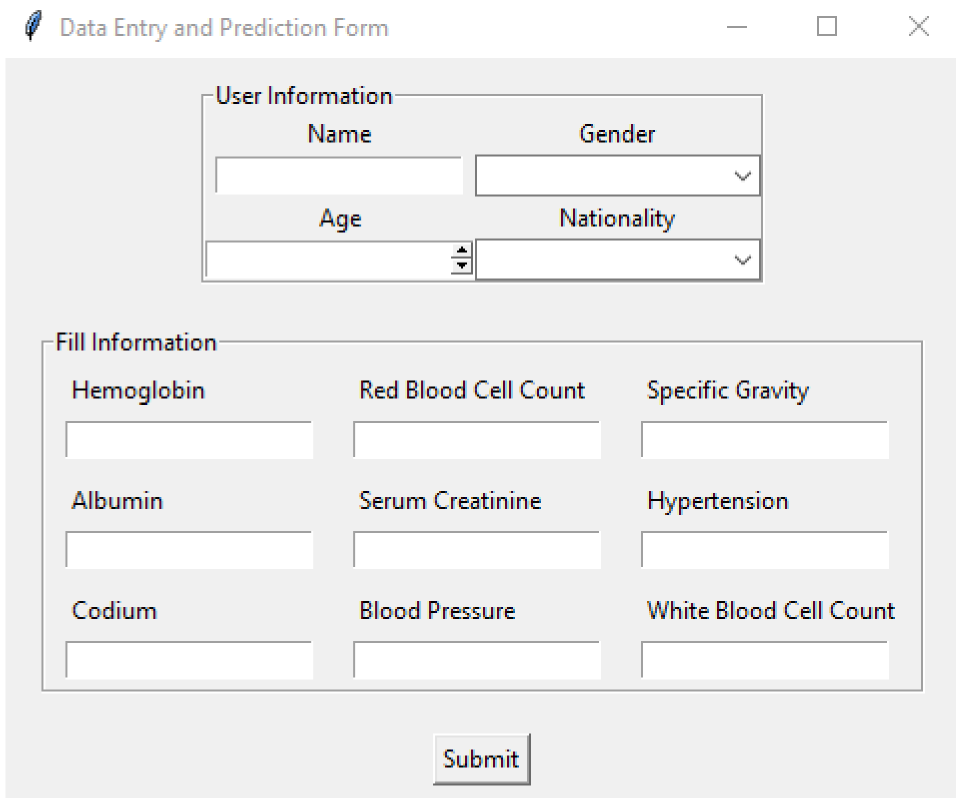


Figure 3. Front page for filling in patient information.

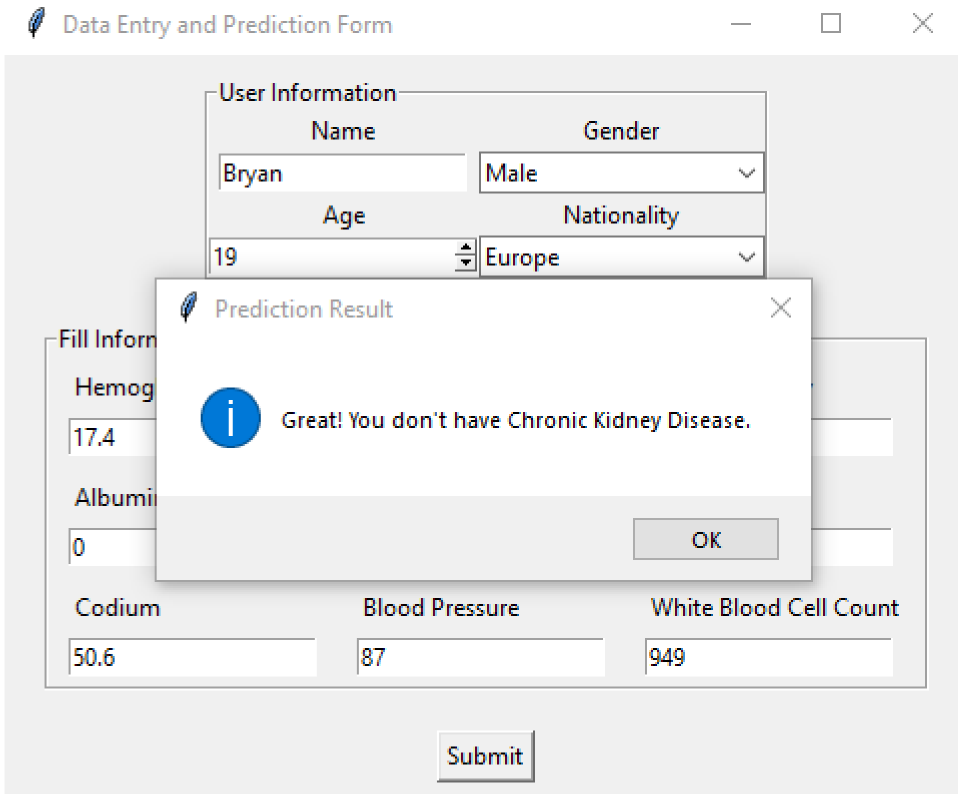


Figure 4. When the patient doesn't have CKD.

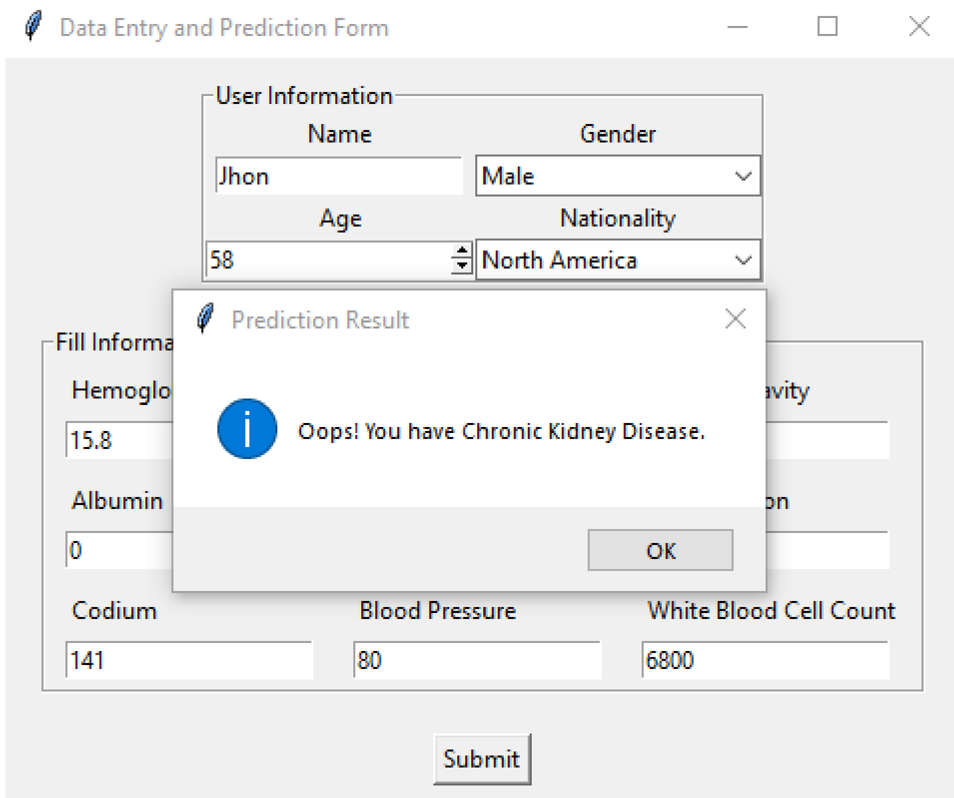


Figure 5. When the patient has CKD.

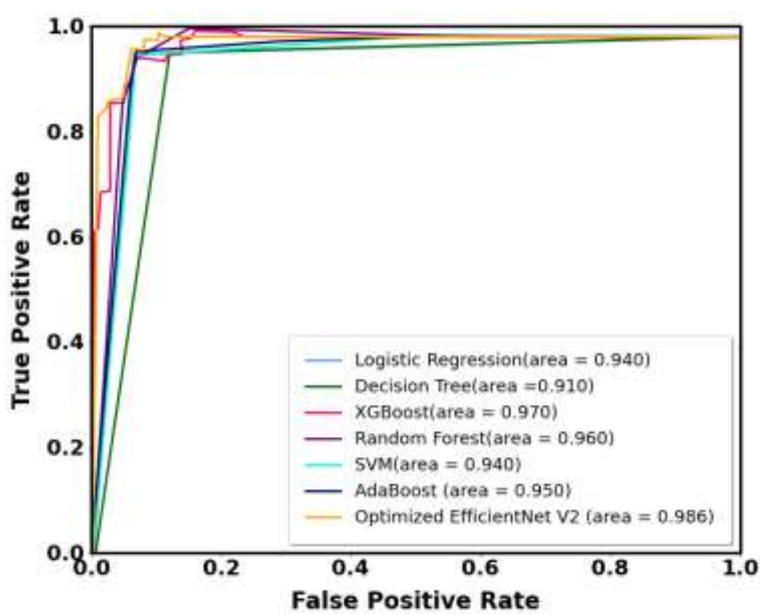


Figure 6. The classifiers' ROC curve after being trained with the entire feature set.

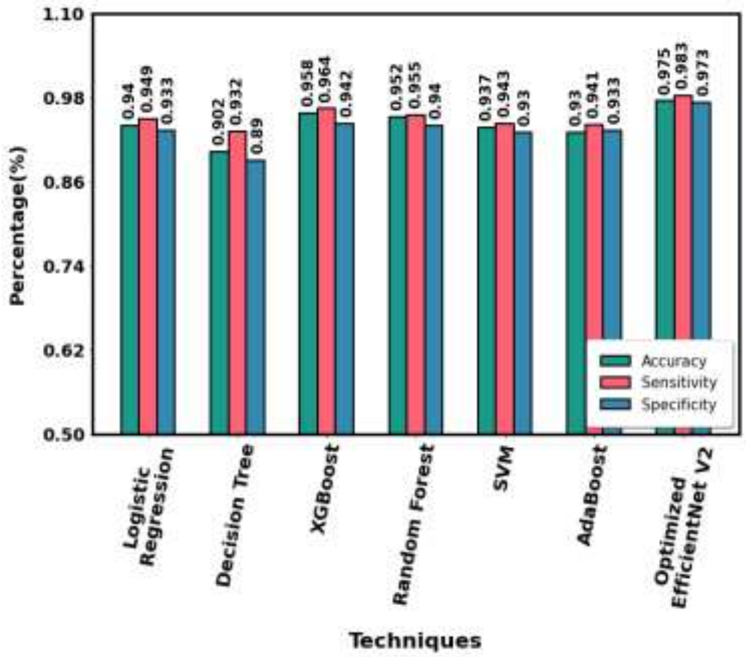


Figure 7. Accuracy, Sensitivity, and Specificity for each classifier without feature selection.

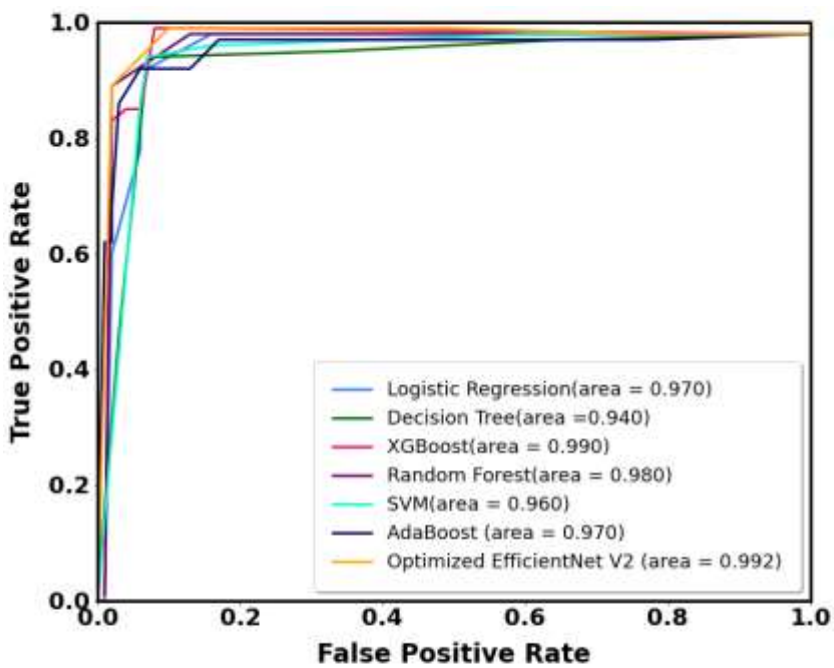


Figure 8. The classifiers' ROC curve after training on a smaller feature set.

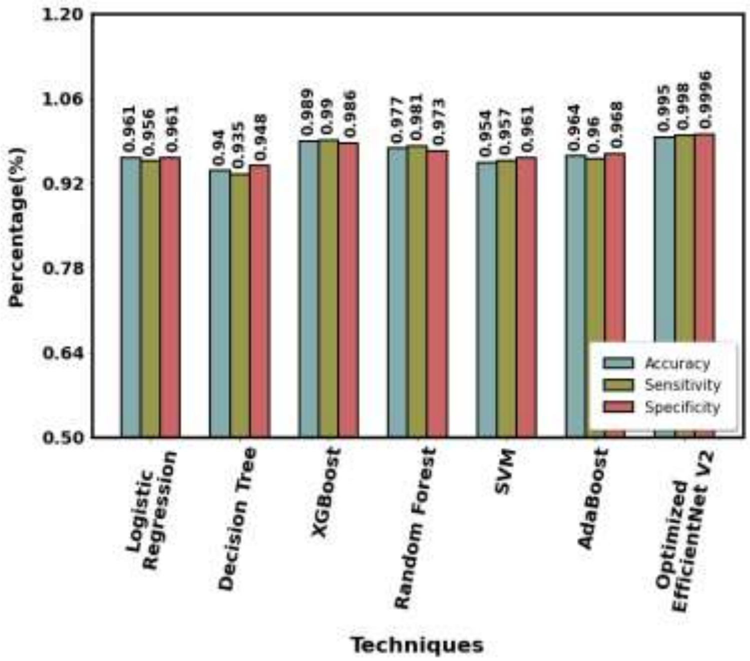


Figure 9. Accuracy, Sensitivity, and Specificity for each classifier after feature selection.

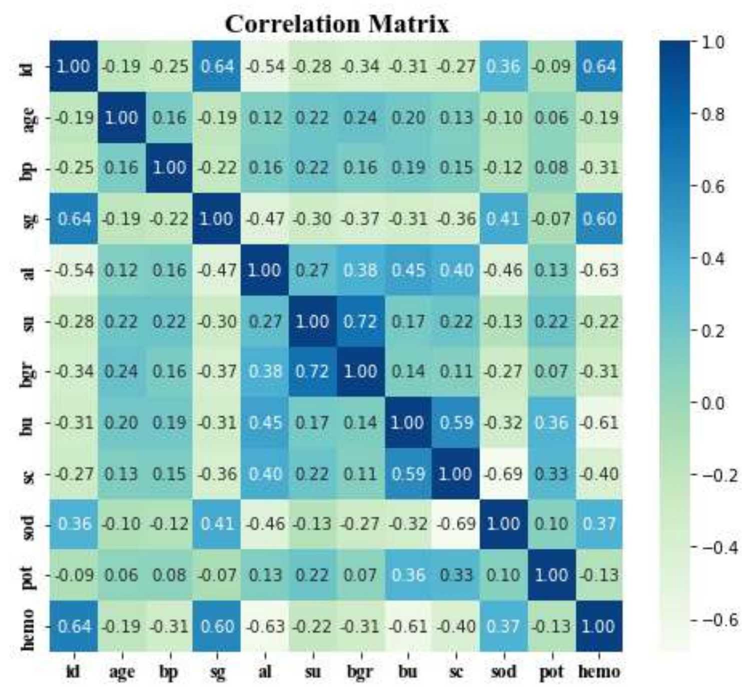


Figure 10. Correlation between different features.

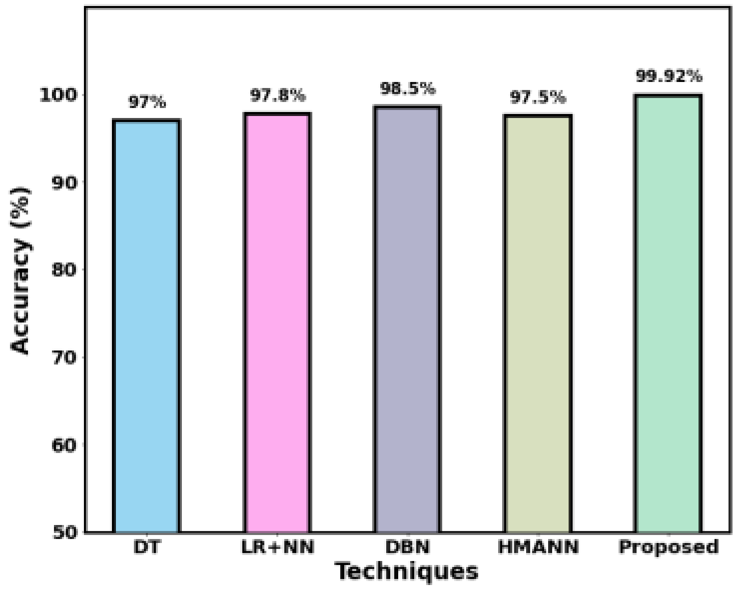
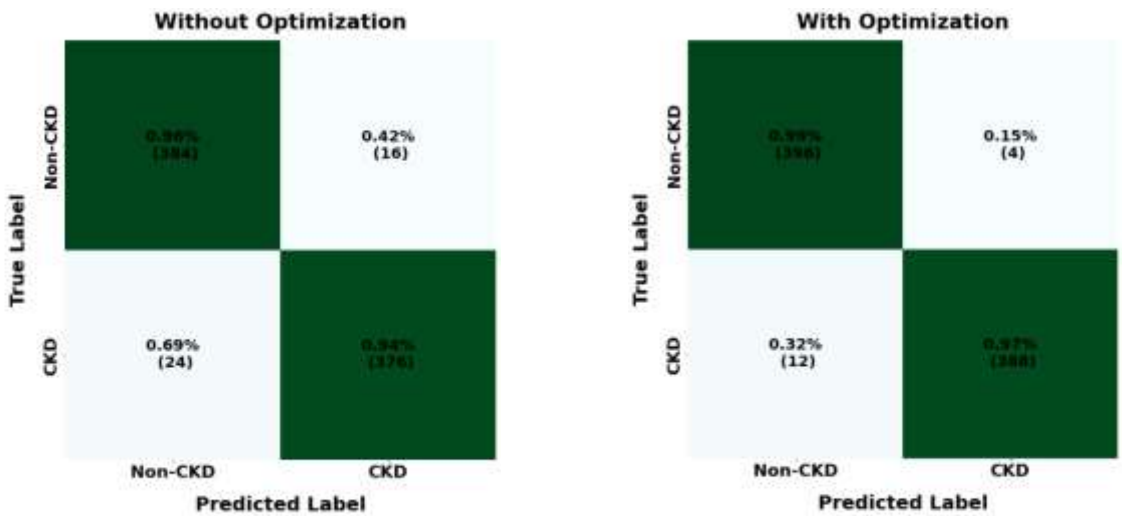
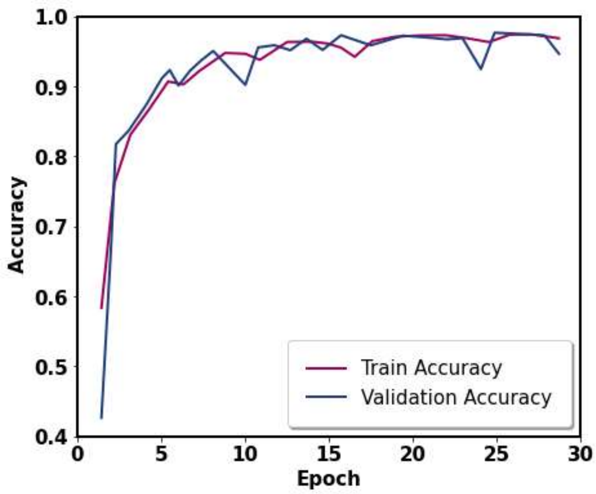


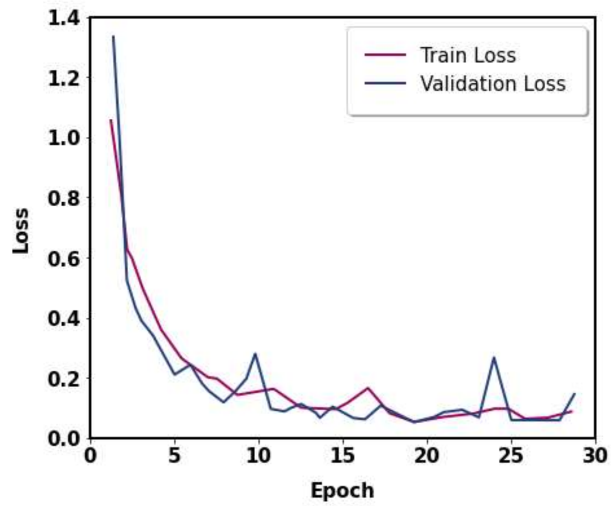
Figure 11. The comparison of proposed and previous methods in CKD.



(a) (b)

Figure 12. Confusion Matrix for (a) Without Optimization, (b) With optimization.





(a) (b)

Figure 13. (a) Training and validation accuracy, (b) Training and validation loss

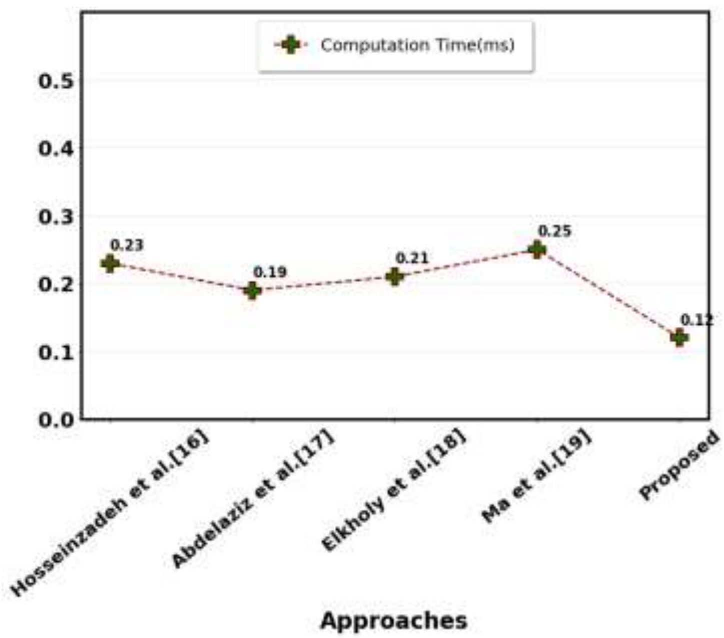


Figure 14. The computation time for the proposed methodology and existing methodologies.

Table 1. Settings for hyper-parameters.

Hyper-Parameter	Setting
Batch size	15
Epochs	850
Activation Function	Relu
Optimizer	Adam
Dropout rate	0.5 to 0.1
Loss	Binary_Crossentropy
Activation output layer	Sigmoid

Table 2. Environment setup of the proposed system.

Resource	Details
CPU	Core i5 Gen6
RAM	8 GB
GPU	4GB
Software	Python

Table 3. Splitting Dataset.

Dataset	Numbers
Training	320 patients
Testing and validation	80 patients

Table 4. Performance of classification techniques without feature selection.

Classifier	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
Decision Tree	0.902	0.932	0.890	0.910
Logistic Regression	0.940	0.949	0.933	0.940
Random Forest	0.952	0.955	0.940	0.960
XGBoost	0.958	0.964	0.942	0.970
AdaBoost	0.930	0.941	0.933	0.950
SVM	0.937	0.943	0.930	0.940
Optimized EfficientNet V2	0.975	0.983	0.973	0.986

Table 5. Performance of classification techniques with feature selection.

Classifier	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
Decision Tree	0.940	0.935	0.948	0.940
Logistic Regression	0.961	0.956	0.961	0.970
Random Forest	0.977	0.981	0.973	0.980
XGBoost	0.989	0.990	0.986	0.990
AdaBoost	0.964	0.960	0.968	0.970
SVM	0.954	0.957	0.961	0.960
Optimized EfficientNet V2	0.995	0.998	0.9996	0.992

Table 6. Overall comparison of proposed and existing methods

References	Approaches	Accuracy
Hosseinzadeh et al. [16]	DT	97
Abdelaziz et al. [17]	LR+NN	97.8
Elkholy et al. [18]	DBN	98.5
Ma et al. [19]	HMANN	97.5
Proposed	Optimized EfficientNet V2	99.92

Table 7. Utilizing the proposed and existing methods.

Methods	Computation Time
Hosseinzadeh et al. [16]	0.23
Abdelaziz et al. [17]	0.19
Elkholy et al. [18]	0.21
Ma et al. [19]	0.25
Proposed	0.12

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A Review: Analyzing Risk Factors and Prediction for Chronic Kidney Disease using Machine and Deep Learning Techniques

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Abstract— **Chronic nephritic illness is another name for chronic kidney disease (CKD). It outlines limitations that impact your kidneys and lower your chances of maintaining good health. Numerous complications, such as elevated blood levels, weak bones, anemia (low blood count), and nerve damage, will be a problem. It is usually possible to prevent chronic uropathy from worsening by early identification and treatment. Between 4.902 and 7.083 million people worldwide are expected to have chronic kidney disease (CKD), requiring renal replacement treatment. The cost-effectiveness of disease prevention measures should be assessed in light of the resources and economic development of the local community. This study covers the research done over the last five years (2019–2023) on machine learning (ML) and deep learning (DL)-based techniques for exact CKD predictions. The study concludes that quick advancements in sensing technologies, machine learning, and deep learning will offer comprehensive, sensible choices for more accurate estimations of CKD prediction. According to projections, CKD will soon require increasingly specialized applications of sensor platforms, ML, and DL techniques, the integration of various sensor modalities with expert knowledge, and the development of hybrid models that combine various ML and DL techniques. This review demonstrates how knowledge-based CKD prediction can sustainably improve products' productivity and quality.**

Keywords— Chronic kidney disease, prediction, deep learning, methods, machine learning, review, dataset.

I. INTRODUCTION

When a patient's kidney function declines, a condition known as chronic kidney disease develops. Their general quality of life consequently declines. One in ten persons worldwide suffers from chronic kidney disease (CKD). CKD is predicted to become the fifth most common cause of mortality globally by 2040 due to its increasing prevalence. It is among the main reasons why medical expenses are so expensive [1-3]. Dialysis and transplantation cost two to three percent of the annual medical budget in high-income countries. Most renal failure patients in countries with low or middle incomes lack adequate access to kidney transplants and life-saving dialysis [4, 5]. It is anticipated that the incidence of renal failure will climb sharply in developing nations like China and India. When renal failure is chronic, it becomes more difficult to eliminate excess fluid from the body's circulation. The body may accumulate hazardous amounts of fluid, electrolytes, and waste products due to advanced chronic renal disease. Complications include excessive anemia, high blood pressure, nerve damage, and weak bones could result from it. The Glomerular Filtration Rate (GFR) is the most reliable measure of renal function [6-8]. The glomerular filtration rate is another tool doctors use to diagnose renal disease (GFR). IT IS A CHALLENGING CLINICAL ASSIGNMENT because CKD is diagnosed based on many symptoms. When examining a patient's symptoms, doctors' knowledge and experience are the main factors that influence their clinical decisions [9-11]. It's getting harder for doctors to keep up with the latest developments in clinical practice as the healthcare system changes and new medications become available.

ML technology provides valid decision-making methodologies for computer-assisted automatic illness detection. To improve the efficiency of the diagnostic process, ML is being utilized to intelligently understand the data that is now accessible and turn it into valuable information. ML has already been utilized to diagnose a wide range of illnesses, evaluate disease features, and evaluate the condition of the human body [12, 13]. Machine learning-based algorithms have been used to diagnose heart disease. Acute renal injury, diabetes, heart disease, retinopathy, and cancer were all diagnosed using ML algorithms generated models. To identify chronic kidney illness, numerous researchers have employed supervised algorithms such as Fuzzy C Means, Random Forest, Naive Bayes, Gradient Boosting (GB), Support Vector Machine (SVM), and Logistic Regression (LR) classifiers.

Additionally, machine learning can lower hospital admission rates, improve healthcare data quality, and save medical costs. Consequently, compared to other more traditional methods, these are more frequently used in diagnostic analytic research [14, 15]. Early prediction and appropriate chronic disease (CD) treatment are the only ways to lower CD mortality. In traditional ML, two distinct steps are involved in the feature-obtaining and categorization procedures. Consequently, standard machine learning techniques are computationally intensive. This makes the conventional method unworkable for real-time diagnostic applications. This review's crucial contribution is,

- In this survey report, from 2020 to 2021, we review the most recent findings related to chronic kidney disease in several areas.

- The main problem-solving categories in CKD include soil parameters, weather forecasting, and deep learning and machine learning techniques. IoT-based applications are also used in CKD.
- We assessed the CKD algorithms' performance based on their accuracy.

The format of this review is as follows: Sections 2 through 5 provide an overview of the research methodologies used to select the primary studies. The category evaluation on CKD is examined and evaluated in Section 6. The limitations and difficulties of CKD are displayed in Section 7. Section 8 brings the article to a close.

II. RISK FACTORS OF CKD

For individual planning and health systems, risk-prediction algorithms are crucial for identifying CKD patients at risk of progressing to ESRD. The entire population and CKD cohorts generate risk-prediction models, which help estimate the likelihood of clinically relevant events like mortality, CKD, CV disease, and ESRD progression. Their validity is undermined, nonetheless, by competing interests like death that must be taken into consideration and loss to follow-up assessment in validating and derivation cohorts. Furthermore, individual GFR trajectory is not included in published models for the progression of CKD. It is not dynamic, which may be the most predictive factor in the risk of ESRD. A categorization tree analysis was conducted using the Avoidance of Renal Insufficiency Project cohort data, which included at least four creatinine measures over one year. The objective was to determine the variables linked to decreased eGFR and their respective contributions to risk.

III. MACHINE LEARNING-BASED TECHNIQUES

It has been demonstrated that ML models work well for both diagnosing and predicting significant illnesses. CKD may be accurately diagnosed using ML, according to several recent studies.

A. *Supervised Learning for CKD Detection*

Venkatesan et al. [16] suggested applying machine learning techniques on a dataset accessible to the public to predict and categorize chronic renal disease. The 400 cases of the CKD dataset were gathered from the Irvine ML Repository, a publically accessible dataset. During pre-processing, the mode technique was utilized to determine missing nominal data, while the mean method was used to estimate missing numeric data. Recursive feature elimination, or RFE, is a technique used to identify the relevant features of the high-importance attributes for predicting chronic kidney disease.

Ghosh et al. [17] suggested using ML methods to predict CKD with extremely high accuracy. An internet data repository is where the dataset was gathered. There are numerous pre-processing methods used to clear this data. Using the dataset that was downloaded from the repository, attributes are selected. Once cleansed and processed, the data is separated into training and test set data. Four machine learning categorization algorithms—SVM, AB, LDA, and GB—are trained on test data to generate predictions.

Jerlin & Perumal [18] introduced the fruit fly optimization algorithm (FFOA) and an effective multi-kernel support vector machine (MKSVM) for categorizing diseases. First, FFOA is utilized to choose the best attributes from the provided feature set. To classify medical data, the attributes selected from the clinical dataset are cleaned and fed into the MKSVM. MATLAB has been used to mimic the suggested categorization approach for CKD. The original CKD dataset from UCI ML repositories, including Kidney Chronic, Hungarian, Cleveland, and Swiss, is then used to test the dataset. According to the investigational outcomes, the proposed CKD classification method outperforms the current hybrid kernel SVM, fuzzy min-max GSO neural network.

TABLE I. DIFFERENT SUPERVISED LEARNING FOR CKD DETECTION.

References	Methods	Advantages	Disadvantages
Venkatesan et al. [16]	XGBoost	It enhances the evaluation of the presented approach.	XGBoost may not handle the raw pixel values efficiently.
Ghosh et al. [17]	SVM, AB, LDA, and GB	It handles high-dimensional feature spaces	It is computationally expensive
Jerlin & Perumal [18]	MKSVM	It is adequate for binary image classification tasks	SVMs are primarily designed for binary classification, which can be a limitation in tasks requiring multi-class image classification

The Table 1 demonstrates the different supervised learning for CKD detection.

B. *Unsupervised Learning for CKD Prediction*

A model for intelligent categorization and prediction was suggested by Elkholy et al. [19]. The classification algorithm for kidney-related disorders is a modified Deep Belief Network (DBN), with Softmax as the activation method and Categorical Cross-entropy as the loss method.

For chronic renal illness, Elkholy et al. [20] suggested an optimized deep belief network (DBN) named "DFS-ODBN" that is built on the Grasshopper's Optimization method (GOA) with a prior Density-based Feature Selection (DFS) method. The suggested approach uses DFS to remove redundant or unnecessary dimensions before the DBN classifier, whose variables are tuned utilizing GOA. Pre-processing, choosing features, and categorizing phases comprise the three stages of the suggested DFS-ODBN structure. They also test the suggested technique with CKD datasets and examine the performance with other assessment metrics.

Ebiaredoh et al. [21] suggested a method that hybrid a cost-sensitive AdaBoost technique with an information-gain-based feature selection algorithm to identify CKD efficiently. Since only a few clinical test attributes would be required for the diagnosis, such a method could reduce both time and money regarding CKD screening. The suggested strategy was tested against popular classifiers and newly suggested CKD prediction techniques. The best classification outcome was achieved by the suggested cost-sensitive AdaBoost classifier, which was trained using the smaller feature set.

TABLE II. DIFFERENT UNSUPERVISED LEARNING FOR CKD DETECTION.

References	Methods	Advantages	Disadvantages
Elkholy et al. [19]	DBN	DBNs can extract hierarchical abstractions from images by capturing features at various granularity levels.	Training DBNs can be computationally expensive and time-consuming.
Elkholy et al. [20]	DFS-ODBN	reducing the dimension of image data, which can enhance the performances	It leads to some information loss.
Ebiaredoh et al. [21]	AdaBoost	Automatically select the most informative features	Adaboost may need to be more accurate in classifying particular things because it depends on noisy data and outliers.

The Table 2 shows the different unsupervised learning for CKD detection.

IV. DEEP LEARNING-BASED TECHNIQUES

It has been demonstrated that deep learning models work well to diagnose and predict severe illnesses.

A. *Convolutional Neural Networks (CNNs) for CKD Detection*

Bhaskar & Manikandan [22] suggested a sensing method for renal illness detection that is automated. To identify the illness, the concentration of salivary urea is tracked. A fresh sensing method is presented to track the amount of urea in the saliva sample. In addition, an SVM technique is integrated with a one-dimensional DL CNN method to analyze the sensor's raw signals. The model's classification accuracy was improved by using the CNN-SVM integrated network.

Convolutional neural networks (CNNs) were suggested by Pavithra & Vanithamani [23] to identify CKD from medical information and compare their results with those of other ML techniques. Since there are some missing data in the given information, the most often occurring category is used to attribute categorical data, and the k-nearest neighbor is used to attribute numerical data. As a result, the optimal technique for autonomously diagnosing CKD from medical information is revealed in this paper.

In order to identify CKD non-invasively from saliva samples, Navaneeth & Suchetha [24] suggested a CNN learning network along with a sensing module. They have been tracking the amount of urea in the saliva sample to identify CKD. Given its many benefits, the salivary diagnostic strategy described in this work is worthwhile to explore. Saliva-based diagnosis is preferred because of how simple and non-invasive the sample extraction process is. Two critical modifications to the traditional CNN model are made to create the suggested learning model. To gradually choose the pertinent characteristics for the categorization, they have included a feature pruning approach and a dynamic pooling approach. The CNN framework is coupled with an SVM method to improve categorization accuracy. The outcomes of the experiments indicate that the characteristics acquired by the suggested network outperform manually extracted features.

TABLE III. DIFFERENT CONVOLUTIONAL NEURAL NETWORKS (CNNS) TECHNIQUES FOR CKD DETECTION.

References	Methods	Advantages	Disadvantages
Bhaskar & Manikandan [22]	CNN-SVM	The combination of CNNs and SVMs can improve the robustness of image classification.	It can be complex and require extensive parameter tuning.
Pavithra & Vanithamani [23]	CNN	Learning relevant features from the data reduces the need for manual feature engineering.	It requires large amounts of labeled data for training.

Navaneeth & Suchetha [24]	SVM	The overfitting issue is handled with the help of the regularization parameters.	SVMs can be sensitive to outliers in the training data.

The Table 3 demonstrates the different convolutional neural networks techniques for CKD detection.

B. Handling Imbalanced Data in Deep Learning

In order to create more accurate predictions, Bhaskar et al. [25] developed an enhanced DL model that integrates a bidirectional LSTM network with a one-dimensional Correlational Neural Network (1-D CorrNN). To leverage both networks' capabilities for the time-series information process, the LSTM framework and the neural method are merged. A CKD sensing module is used to train and evaluate the suggested model. Because DL algorithms can identify the best attributes from the input data, their use helps to increase detection accuracy.

Silveira et al. [26] introduced a manual and automatic augmentation-based oversampling method. The borderline-SMOTE, synthetic minority oversampling technique (SMOTE), and borderline-SMOTE SVM were tested. We put into practice models based on the random forest, multi-class AdaBoosted DTs, and decision tree (DT) algorithms. We additionally utilized the approaches of overall local precision and local class precision for dynamic classifier selection; additionally, they applied META-DES, k-nearest oracles-union, and k-nearest oracles-eliminate for dynamic ensemble selections.

Kafi et al. [27] presented a 1D Convolutional Neural Network (1D CNN) based CKD detection technique that addresses the issues above and considerably increases diagnosis accuracy. This work makes use of the CKD Dataset from the UCI ML Repository. Missing data has been handled using a precise non-parametric missing data imputation method called MissForest imputation. To handle anomalies, memory-efficient Isolation Forest has also been used.

TABLE IV. HANDLING IMBALANCED DATA IN DEEP LEARNING TECHNIQUES.

References	**Methods**	**Advantages**	**Disadvantages**
Bhaskar et al. [25]	1-D CorrNN + BiLSTM	BiLSTMs are capable of handling variable-length sequences	It is computationally expensive. This increased complexity can make them less suitable for real-time applications.
Silveira et al. [26]	DT	Decision Trees can handle noisy data to some extent.	Decision Trees are prone to overfitting, especially when they are deep and complex.
Kafi et al. [27]	1D CNN	1D-CNNs operate on a single dimension; they typically require less computational power	Information loss occurs

The Table 4 shows the handling imbalanced data in deep learning techniques.

V. IOT-BASED TECHNIQUES

Using IoT multimedia data, Hosseinzadeh et al. [28] suggested a predicting approach for CKD and its severity. Choosing various features based on doctors' clinical experiences and observations and prior research for CKD in various multimedia datasets is done to assess the effectiveness indicators of CKD forecasting. This is done because the volume of IoT multimedia information is typically massive, and the influencing attributes on CKD are enormous. In contrast to Multi-Layer Perception (MLP), SVM, and NB classifiers, the experimental findings show that the applied dataset with the suggested chosen attributes.

To deliver efficient healthcare, Lakineni et al. [29] presents an online platform that supports healthcare judgment in forecasting chronic kidney disease (CR). The three steps the suggested model takes to predict CKD are gathering, preparing, and classifying clinical data. The logistic regression (LR) approach divides the data instances into CKD and non-CKD categories. Furthermore, the LR's settings are adjusted using the adapted training rate optimization techniques and the Adaptive Moment Estimation (Adam) algorithm. A reference CKD dataset is used to assess the efficacy of the recently suggested model.

Arulanthu & Perumal [30] developed patients with efficient medical care and suggested an OMDSS to forecast CKD. There are three primary phases to the operation of the OMDSS that are being presented. The necessary data is gathered from multiple sources and stored in the CDS earlier. The second phase involves pre-processing. The predictive model that uses LR-A is implemented towards the end. The benchmark CKD dataset is utilized to test the suggested OMDSS, and the findings are confirmed using a range of validation criteria.

TABLE V. DIFFERENT IOT-BASED TECHNIQUES FOR CKD DETECTION.

References	Methods	Advantages	Disadvantages
Hosseinzadeh et al. [28]	DT	Capture non-linear relationships in image data.	Image data typically requires extensive pre-processing before being suitable for Decision Trees.
Lakineni et al. [29]	LR	LR is less prone to overfitting	LR is primarily designed for binary classification.
Arulanthu & Perumal [30]	OMDSS	OMDSS helps reduce the dimensionality of image data	While dimensionality reduction can be an advantage, it can also lead to the loss of some details and information

The Table 5 shows the different IoT-based techniques used in CKD detection.

VI. DETAILED DISCUSSION OF ML AND DL METHODS

The role of DL and ML techniques in CKD is the subject of this review. These algorithms evaluated CKD predictions from public datasets such as the UCI CKD dataset. The reviewed systems are represented in Table 6.

TABLE VI. COMPARISON OF CHRONIC KIDNEY DISEASE TECHNIQUES BASED ON ACCURACY.

References	Methods	Datasets	Accuracy Measure
Venkatesan et al. [16]	XGBoost	CKD dataset from Irvine ML Repository	98.00%
Ghosh et al. [17]	SVM, AB, LDA, and GB	CKD dataset from Irvine ML Repository	99.56%, 97.91%, 97.91%, 99.80%
Jerlin & Perumal [18]	MKSVM	Chronic Kidney dataset, Cleveland, Hungarian, and Switzerland dataset	98.5%, 90.42904%, 89.11565%, 86.17886%
Elkholy et al. [19]	DBN	-	98.5%
Elkholy et al. [20]	DFS-ODBN	-	99.75%
Ebiaredoh et al. [21]	AdaBoost	-	99.8%
Bhaskar & Manikandan [22]	CNN-SVM	-	98.04%
Pavithra & Vanithamani [23]	CNN	Chronic Kidney Diseases Dataset	99.12%
Navaneeth & Suchetha [24]	CNN-SVM	-	96.12%
Bhaskar et al. [25]	LSTM+1-D CorrNN	Chronic Kidney Diseases Dataset	98.08%
Silveira et al. [26]	DT	-	98.99%
Kafi et al. [27]	1D CNN	Chronic Kidney Diseases Dataset	99.21%
Hosseinzadeh et al. [28]	DT	-	97%
Lakineni et al. [29]	LR	Chronic Kidney Diseases Dataset	
Arulanthu & Perumal [30]	OMDSS	CKD dataset	97.75%

From the above research, machine learning-based techniques such as XGBoost, SVM, AB, LDA, and GB, MKSVM, DBN, DFS-ODBN, AdaBoost perform well, but in comparing these three techniques, the SVM, AB, LDA, and GB achieved 99.56%, 97.91%, 97.91%, 99.80% accuracy in CKD prediction. As well as utilizing deep learning-based techniques of CNN-SVM, CNN, LSTM+1-D CorrNN, DT, 1D CNN, the CNN obtained 99.12%of accuracy.

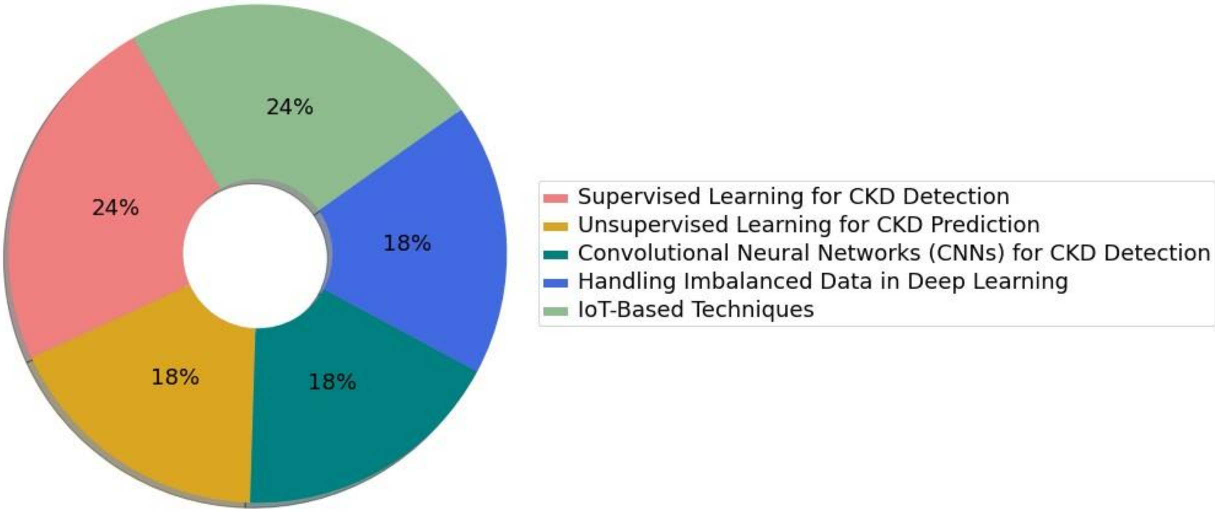

Fig. 1. DL and ML techniques utilized in CKD prediction.

The Figure 1 shows the machine and deep learning techniques used research mentioned in this review.

VII. CHALLENGES AND LIMITATIONS

1. The accuracy of CKD prediction models heavily relies on the quality and quantity of available data. Data may often need to be completed, biased, or updated, making it challenging to build robust predictive models.
2. CKD datasets are often imbalanced, with a disproportionate number of non-CKD cases compared to CKD cases.
3. Complex machine learning models may provide accurate predictions but need more interpretability. Clinicians must understand why a model makes a particular prediction to trust and act upon.
4. Developing models that generalize well to diverse patient populations and healthcare settings is challenging. Overfitting to the training data can lead to poor performance on new data.
5. It's crucial to validate prediction models in natural clinical settings to ensure they provide meaningful and actionable information to healthcare providers.

VIII. CONCLUSION

Some of the most significant difficulties caused by CKD have been outlined in this review. Early disease stages are clinically silent, preventing early intervention to limit the disease's course and allowing CKD and ESKD to continue. Patients with CKD are already more likely to experience cardiovascular-related mortality and morbidity in the later stages of the disease when clinical symptoms are manifest. As a result, advanced phases of CKD and ESKD are linked to unfavorable outcomes and a heavy clinical and financial burden.

Future Directions

The suggested model's testing on limited data sets was one of its drawbacks. In the future, large amounts of increasingly complex CKD data will be gathered to determine the severity of the disease and enhance the model's performance. The clinical information that pathologists' specialists should provide. In the future, an extensive clinical data set based on inorganic phosphorus concentration, hyperparathyroidism, acid-base parameters, and nighttime urination will be used to assess the efficacy of the suggested model. To verify the prediction accuracy, more characteristics will be implemented to obtain a more comprehensive understanding of the informative parameters associated with the CKD disease.

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