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A Neutrosophic Logic Ruled Based Machine Learning Approaches for Chronic Kidney Disease Risk Prediction

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Abstract

Chronic kidney disease (CKD) represents a significant global health challenge in society, and early detection of risk is essential for on-time treatment and intervention. This research suggests a novel machine-learning technique to create a reliable and accurate CKD risk prediction model by combining neutrosophic logic with various classification algorithms. We use neutrosophic logic to address the inherent imprecision and uncertainty in medical data, resulting in a more realistic portrayal of real-world scenarios. We measure the effectiveness of the proposed neutrosophic logic-based models using various metrics, including precision, specificity, and sensitivity. The results show that the neutrosophic logic method is better than traditional machine learning methods at finding people who are likely to develop CKD because it is more accurate and stable. This study illustrates the potential for incorporating neutrosophic logic into machine learning frameworks to improve risk prediction in medical fields.

Keywords: Classifier; Kidney Disease; Neutrosophic Logic; Risk Prediction Model

1. Introduction

Chronic kidney disease (CKD) represents a significant public health challenge. This condition arises when the kidneys lose their ability to perform essential functions, such as regulating blood pH, water, and electrolyte balance. The kidneys remove waste products through urine as the body's natural filtration system. CKD not only impairs kidney function but can also impact surrounding organs, exacerbating health complications. The emerging field of health informatics, which focuses on managing health data, encompasses the collection, storage, retrieval, and analysis of medical information. It enhances communication and maximizes healthcare resources and insights, guided by ethical principles rooted in information science to address complex health challenges [1, 2]. Renal diseases, including CKD, primarily result from nephron dysfunction. Essential processes, such as balancing pH, hydration, and sodium levels, become compromised when kidney function declines. The kidneys, which serve as a biological filter, lose their ability to remove waste, causing long-term organ deterioration. CKD progressively advances through five stages, with minimal symptoms in the early stages, making detection challenging. Early diagnosis, however, is critical. The fourth stage severely compromises kidney function, requiring timely intervention to improve kidney health. In the fifth and final stage, the kidneys fail, rendering them unable to clear excess waste and fluids from the body. This stage, known as kidney failure, requires dialysis or kidney transplantation, as no other cure is available.

The asymptomatic nature of CKD in its early phases limits early detection and narrows preventative options. Early diagnosis and treatment are essential to controlling CKD progression. Identifying risk factors and symptoms at the onset can reduce disease incidence and manage health complications in CKD patients. CKD patients who remain undiagnosed face worsening health outcomes. Early medical intervention is crucial; procedures like organ transplantation and dialysis, when conducted under professional supervision, can lower mortality rates. Routine medical checkups, especially for monitoring blood pressure and managing diabetes, are the best way to reduce CKD risk. Physicians should maintain comprehensive records of patients' CKD histories, ensuring data completeness for accurate diagnoses and effective treatment planning.

In recent years, CKD cases have risen due to population growth and lifestyle factors [3, 4]. Recovery from renal diseases is challenging [5, 6]. Image-based feature extraction is also helpful in identifying renal conditions. Studies [7, 8] have utilized computer-aided diagnosis (CAD) systems to analyze kidney characteristics for early disease detection. Researchers have used machine learning (ML) methods to predict CKD risk [9,10,11,12]. Central to artificial intelligence (AI), deep learning develops algorithms enabling computers to learn patterns [13, 14]. Research in [15, 16] compares various ML algorithms, while [17, 18, 44] proposes using MATLAB with a limited dataset to detect early-stage diseases by implementing learning algorithms. Researchers [19,20,21] have also applied data mining techniques to accurately identify CKD.

Machine learning heavily depends on convolutional learning techniques and systems. The term "network" in this context generally refers to computer-based systems that mimic neural processes, facilitating machine learning [22, 23]. Early detection of conditions allows healthcare providers to implement preventive measures to reduce potential risks [24]. The proposed approach ranks risk factors based on their significant impact on kidney health [25, 26]. Artificial intelligence (AI), also known as knowledge-based systems, enables computers to perform decision-making processes like human experts. These systems use sophisticated algorithms to address complex challenges [27, 28, 45].

Renal disease poses a global health challenge, particularly in regions like Taiwan, where the Taiwan Society of Nephrology has reported a substantial increase in renal disease cases,

surpassing one hundred thousand. Statistics from the United States Renal Data System (USRDS) also indicate that Taiwan leads globally in end-stage kidney disease incidence and mortality rates [29, 30]. We recommend dietary management to lower the risk of kidney failure [31]. Due to its asymptomatic nature, renal disease often goes undiagnosed until advanced stages, limiting primary prevention options [32, 33]. Early detection and treatment are, therefore, essential for managing chronic kidney disease (CKD) progression [34].

An adaptive intelligent model reference system and a feed-forward neural network adaptable to fluctuating conditions could address this challenge. Fuzzy logic (FL) provides decision-making capabilities like human reasoning, preserving several properties from classical logic systems [36]. Expert systems, incorporating specialist knowledge about specific diseases, enable computers to make accurate health assessments and are applicable across a wide range of medical and non-medical fields [37–40]. These systems leverage accumulated information to aid users in making informed decisions and reaching conclusions after performing numerous evaluations. Intelligent machine designs, tailored for real-time applications, often build such systems, achieving success rates above 70% in various practical scenarios [41–43].

Chronic kidney disease (CKD) is a prominent public health concern. It arises when kidney function deteriorates, affecting the body's ability to regulate pH, water, and electrolyte levels. The kidneys, functioning as natural blood filters, expel waste via urine, but CKD can impair these processes and damage neighboring organs. The prevalence of kidney disease has increased significantly due to factors like lifestyle habits and population growth. Kidney disease recovery remains a substantial challenge for affected individuals [2–4].

2. Literature survey

Various studies have applied machine learning and expert systems for diagnosing and predicting kidney diseases. For example, Akgundogdu et al. [23] suggested a neuro-fuzzy inference system to aid in renal failure diagnosis. Babalola [24] developed an online expert system for kidney disease diagnosis and management, while Boukenze [25] suggested a predictive model for chronic kidney disease using data mining and classification methods. Rivera [26] introduced a mobile expert system based on fuzzy logic for diagnosing kidney diseases, and Ahmed et al. [27] also used a fuzzy expert system approach. Yadollahpour [28] created an ANFIS-based decision support system to predict CKD progression, while Muslim [29] implemented a Mamdani fuzzy inference system for CKD diagnosis. In addition, Polat et al. [30] employed support vector machines with feature selection for CKD diagnosis, and Subasi et al. [31] used a random forest model for the same purpose. Gharibdousti et al. [32] focused on CKD prediction through data mining, and Chen et al. [33] introduced two fuzzy classifiers for diagnosing CKD patients. Abdelaziz et al. [34] combined IoT and cloud computing in a machine-learning model for CKD prediction within intelligent cities. Almansour et al. [35] utilized neural networks and support vector machines to forecast CKD.

3. Preliminaries

3.1. Crisp Sets

A crisp set is a fundamental idea in set theory, wherein each element of the universal set is either a member of the set or not. The membership of an element in a crisp set is defined by a membership function:

$$\mu_A(x) = \text{if } \begin{cases} 1, x \in \text{A} \\ 0, x \notin \text{A} \end{cases}$$

3.2. Fuzzy Sets

A fuzzy set is a mathematical construct proposed by Lotfi A. Zadeh in 1965 to characterize sets having indistinct boundaries, allowing elements to possess differing levels of membership. In contrast to crisp sets, which have binary membership (0 or 1), fuzzy sets permit partial membership as determined by a membership function:

$\mu_A(x): U \to [0,1]$where:

- $\mu_A(x) = 1$ represents that $x \in A$.
- $\mu_A(x) = 0$ represents that $x \notin$ A.
- $0 < \mu_A(x) < 1$ represents partial membership, meaning x belongs to A to some degree.

3.3 Neutrosophic set

A neutrosophic set is a mathematical framework introduced by Florentin Smarandache in 1999 to handle uncertainty, vagueness, and indeterminacy in information. It extends fuzzy set theory by incorporating three degrees of membership for each element, rather than just one.
Each element in a neutrosophic set is characterized by three independent membership values $\ddot{T}$, $\ddot{I}$, $\ddot{F}$:
For every element ∈ U , the condition $0 \leq \ddot{T}_{\ddot{A}}(x) + \ddot{I}_{\ddot{A}}(x) + \ddot{F}_{\ddot{A}}(x) \leq 3$

Formally, a neutrosophic set A is defined as:

$A = (x, \left(\ddot{T}_{\ddot{A}}(x), \ddot{I}_{\ddot{A}}(x), \ddot{F}_{\ddot{A}}(x) \right) : x \in X$. where $\ddot{T}_{\ddot{A}}(x)$,$\ddot{I}_{\ddot{A}}(x)$,$\ddot{F}_{\ddot{A}}(x)$ is truth, Indeterminacy and falsity membership degree

4. Material and method

In this research article, we designed a neutrosophic -based machine-learning model to predict the probability of CKD. Here, we have employed data from the dataset we collected from the Kaggle website(www.kaggle.com). The data sheet included patient-level data that involved many medical and lab variables regarding CKD; some of the relevant medical and laboratory variables that might be involved in such research are age, specific gravity, random blood glucose, blood pressure, sodium, potassium, hemoglobin, red &white blood cell count. The neutrosophic model was chosen as it can

capture the natural uncertainty and imprecision that comes with medical data, making it very suitable for healthcare applications where some boundary cases cannot be classified easily. Preprocessing involved handling missing values and outliers, with normalization or standardization applied where necessary to all variables. Clinical thresholds and ranges are thus employed to set neutrosophic membership functions for the variables; however, categories like low, medium, and high may apply based on each variable's standard medical interpretation. This framework for a neutrosophic-based machine learning model demonstrates how integration between neutrosophic logic and machine learning could enhance the interpretability and effectiveness of a predictive model for CKD.

Neutrosophic Feature Selection

Features initially established in a system could have been both relevant and irrelevant to the task. In this sense, feature selection methods can filter out redundant and unwanted features that often form part of the system; these methods could be based on a filter, wrapper, or an embedding method. Neutrosophic Sets (NS), a generalization of crisp, fuzzy, and intuitionistic sets, assist individuals in making more informed decisions by illustrating the interplay between truth, falsehood, and indeterminacy. This interaction mirrors the uncertain and vague nature of human thought processes. Raut.at.el published numerous research papers related to Neutrosophic and Fermatean Neutrosophic Sets [44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57]. However, traditional Multi-Criteria Decision Making (MCDM) methods often overlook such nuanced data. By using an analytical hierarchy process to combine feedback from developers and users in a neutrosophic environment, we can fix the fact that knowledge isn't always accurate or consistent. This will also enhance the system's dependability across all its components.

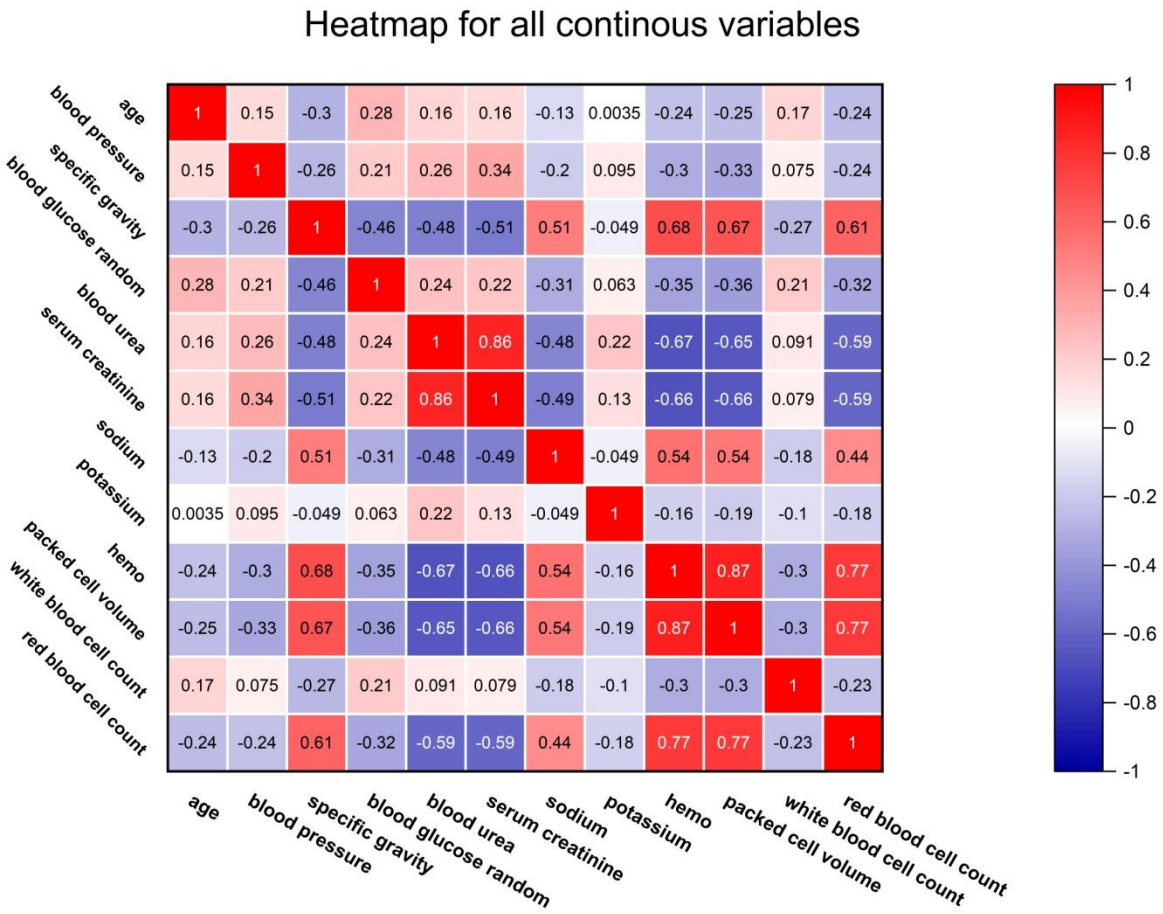


Figure 1 Heat map showing the correlation between the features

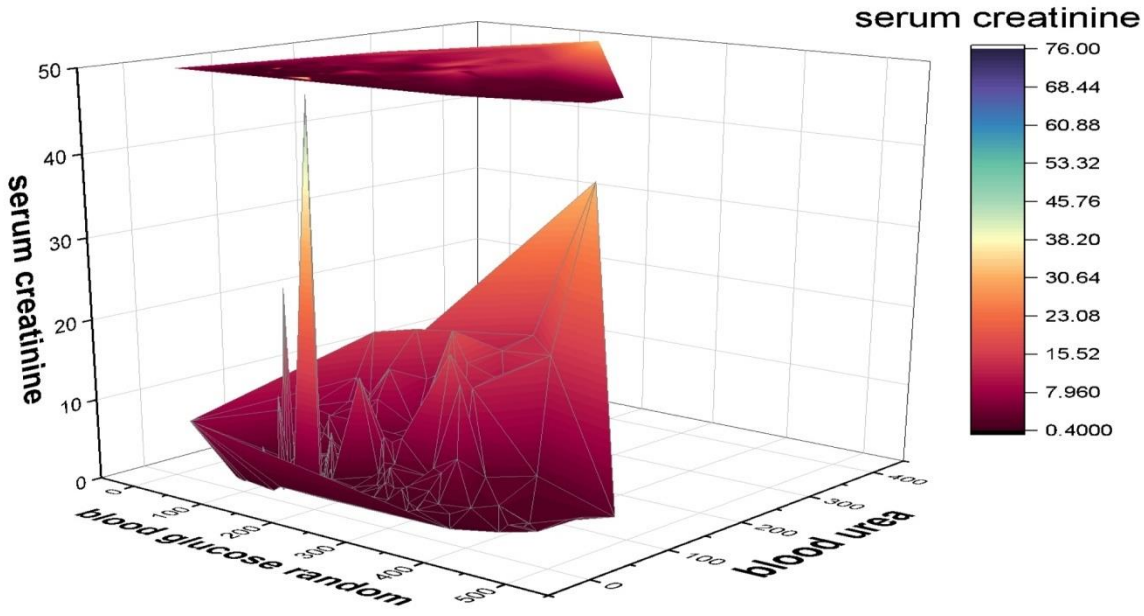


Figure2 3D surface plot for blood urea serum creatinine & blood glucose

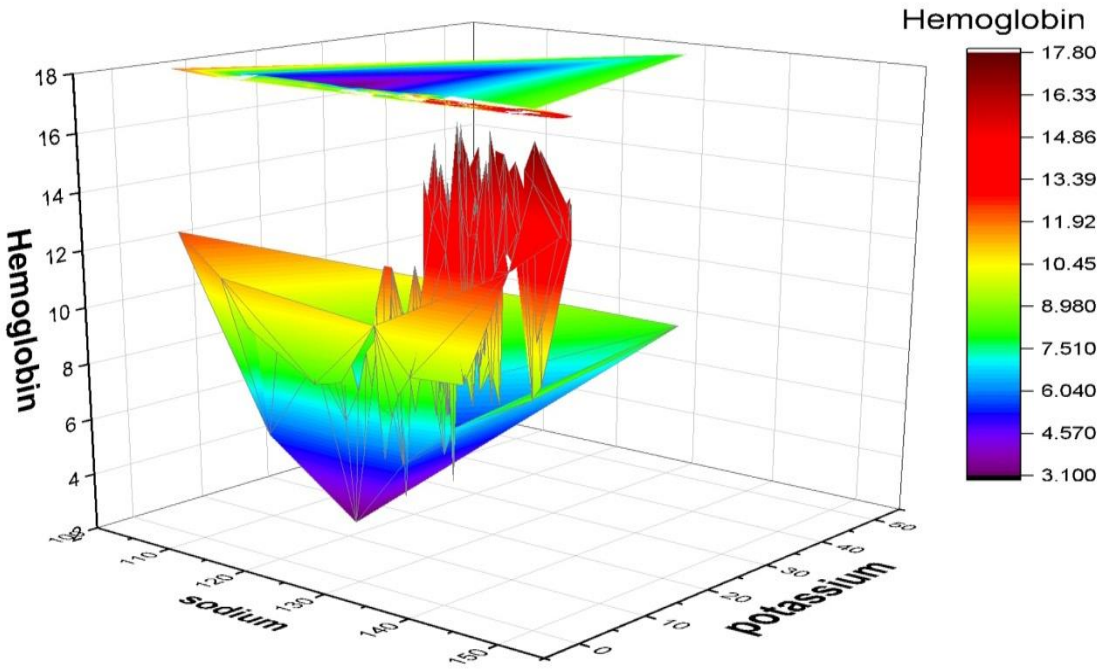


Figure 3 3D Surface plot for Hemoglobin potassium & Sodium

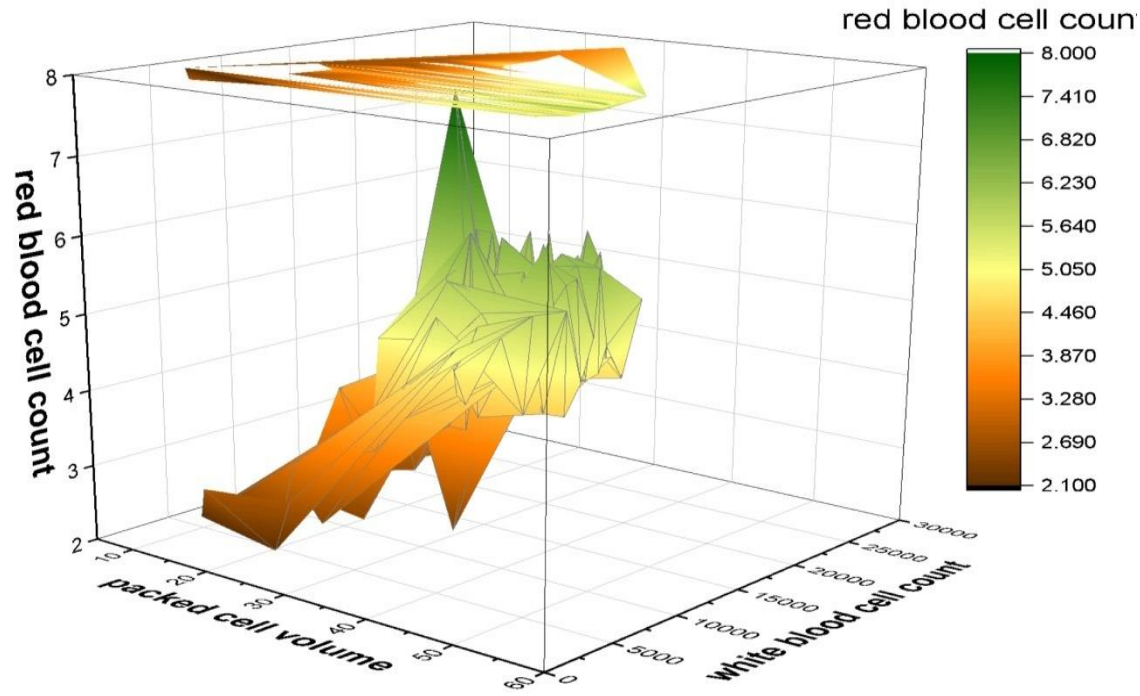


Figure 4 3D Surface plot for WBC, RBC&PCV

Table 1 Distribution of clinical parameters among CKD and NOCKD patients.

Variable	Group	Mean	Median	SD	P
age	CKD	54.54	59	17.3889	<0.001
	NOCKD	46.517	46	15.63114	
blood pressure	CKD	79.63	80	15.23405	<0.001
	NOCKD	71.351	70	8.5435	
specific gravity	CKD	1.01	1.01	0.00463	<0.001
	NOCKD	1.022	1.02	0.00251	
blood glucose random	CKD	175.42	143.5	92.08222	<0.001
	NOCKD	107.722	107.5	18.56474	
blood urea	CKD	72.39	53	58.58724	<0.001
	NOCKD	32.799	33	11.45046	
serum creatinine	CKD	4.41	2.25	6.95028	<0.001
	NOCKD	0.869	0.9	0.25509	
sodium	CKD	133.9	136	12.40283	<0.001
	NOCKD	141.731	141	4.81787	
potassium	CKD	4.88	4.3	4.32155	0.136
	NOCKD	4.338	4.5	0.58726	
hemo	CKD	10.65	10.9	2.18579	<0.001
	NOCKD	15.188	15	1.27754	
white blood cell count	CKD	9069.54	8800	3580.5213	<0.001
	NOCKD	7705.59	7500	1839.771	
red blood cell count	CKD	3.95	3.9	0.8653	<0.001
	NOCKD	5.379	5.3	0.5961	

The relationship among the variables was shown using a heatmap(figure 1).Table 1, represented as mean ± standard deviation, indicates a significant difference between the patients in the CKD and NOCKD groups for all parameters except potassium, which has a p-value of 0.136. The age was calculated to be higher in CKD patients at 54.54 ± 17.39 in comparison with NOCKD patients with an age of 46.52 ± 15.63(P<0.001). Blood

pressure was also higher among the patients of CKD, 79.63 ± 15.23, compared to the patients of NOCKD, 71.35 ± 8.54(P<0.001). Specific gravity was also lower in the CKD patients, 1.01 ± 0.0046 compared to 1.022 ± 0.0025 in the patients of NOCKD, and represented kidney dysfunction Ing. Random blood glucose was highly raised in the patients of CKD, 175.42 ± 92.08, as against 107.72 ± 18.56(P<0.001) in the patients of NOCKD, indicating poor glucose regulation among the former. Blood urea levels in CKD patients averaged 72.39 ± 58.59, which is much higher than 32.80 ± 11.45(P<0.001) in NOCKD. At the same time, serum creatinine was markedly elevated in CKD patients at 4.41 ± 6.95 compared to 0.87 ± 0.26(P<0.001) in NOCKD, indicating impaired kidney function. There is a lower sodium level seen in patients with CKD, which was at 133.9 ± 12.40 compared to NOCKD, while potassium levels showed no statistical difference, with CKD being at 4.88 ± 4.32 while NOCKD stood at 4.34 ± 0.59. Hemoglobin levels presented a reduction in CKD patients at 10.65 ± 2.19 compared to NOCKD, at 15.19 ± 1.28, hence developing anemia. The patients with CKD had a higher WBC count than NOCKD with counts at 9069.54 ± 3580.52 versus NOCKD 7705.59 ± 1839.77 and decreased RBC count at 3.95 ± 0.87 as against 5.38 ± 0.60 recorded for NOCKD suggesting that they had inflammation besides the RBC being relatively produced less. Figure 2, figure 3 figure 4 shows the 3-dimensional relationship among the variables.

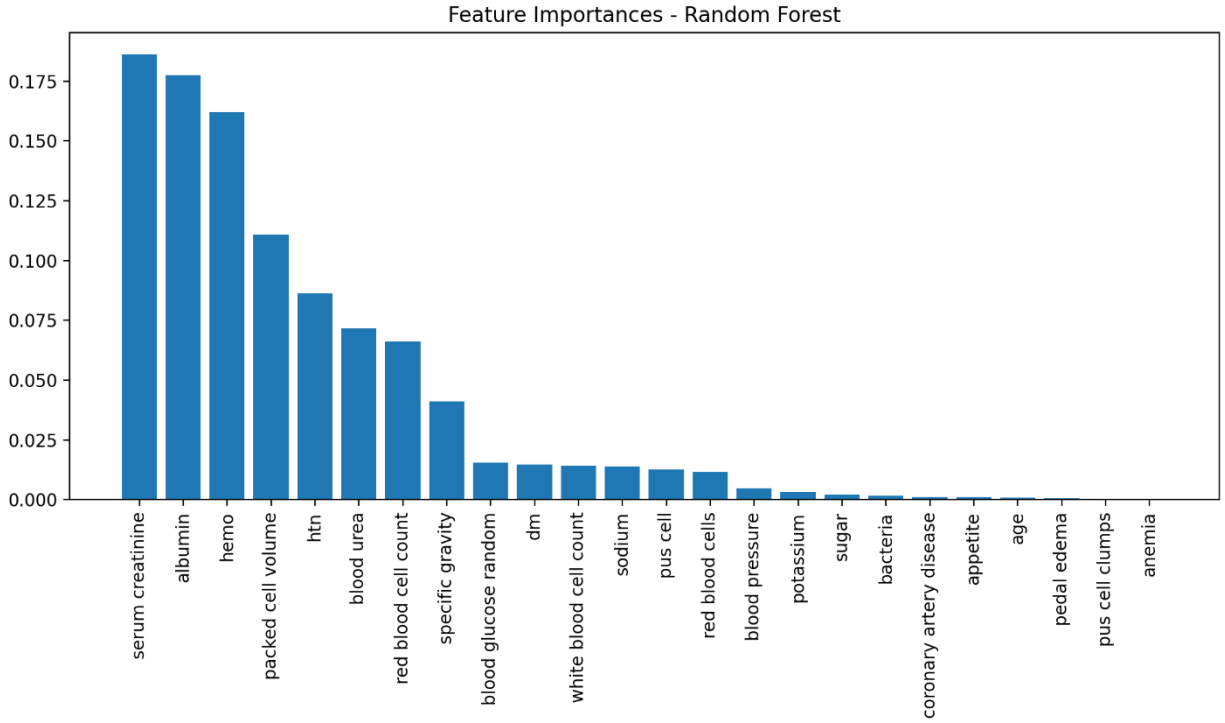
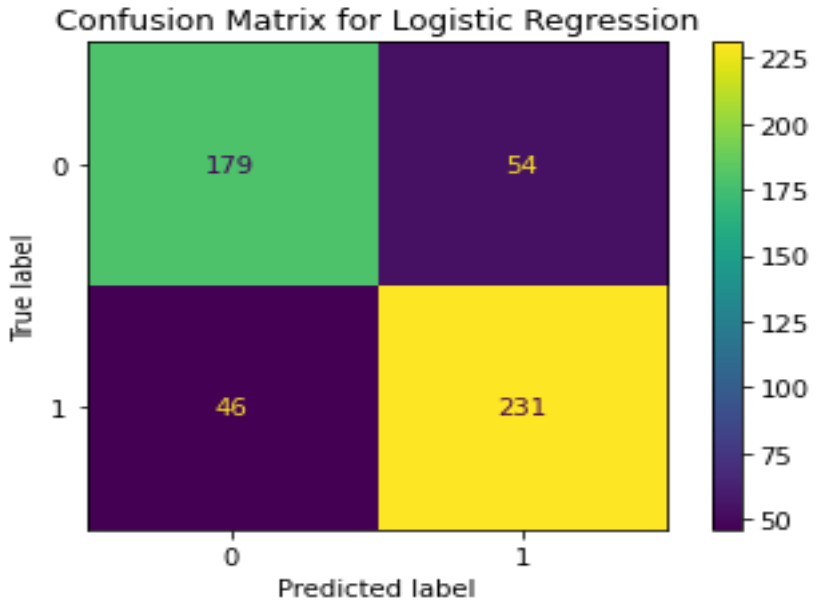


Figure 5 Variable importance plot for Random Forest

Table 2 Neutrosophic Based evaluation matrices for machine learning models.

Matrices	Navie Bays	95% CI	KNN	95% CI	SVM	95% CI	Logistic Regression	95% CI	Random Forest	95% CI
Accuracy	0.892	(0.865, 0.919)	0.839	(0.825, 0.929)	0.847	(0.834, 0.930)	0.804	(0.734, 0.820)	0.892	(0.834, 0.920)
Sensitivity	0.896	(0.861, 0.931)	0.881	(0.821, 0.931)	0.877	0.861, 0.941	0.834	0.811, 0.931	0.877	0.851, 0.931
Specificity	0.888	(0.847, 0.929)	0.790	(0.747, 0.919)	0.811	(0.734, 0.870)	0.768	(0.734, 0.820)	0.905	(0.834, 0.940)
F1 Score	0.9	(0.874, 0.926)	0.833	(0.824, 0.896)	0.862	(0.834, 0.920)	0.822	(0.814, 0.920)	0.883	(0.834, 0.910)
PPV (Precision)	0.905	(0.871, 0.939)	0.856	(0.811, 0.889)	0.847	(0.824, 0.920)	0.811	(0.804, 0.920)	0.889	(0.814, 0.916)
NPV	0.877	(0.834, 0.920)	0.848	(0.834, 0.920)	0.848	(0.824, 0.928)	0.796	(0.734, 0.820)	0.895	(0.834, 0.926)
MCC	0.713		0.769		0.690		0.303		0.78	


Confusion Matrix for Logistic Regression
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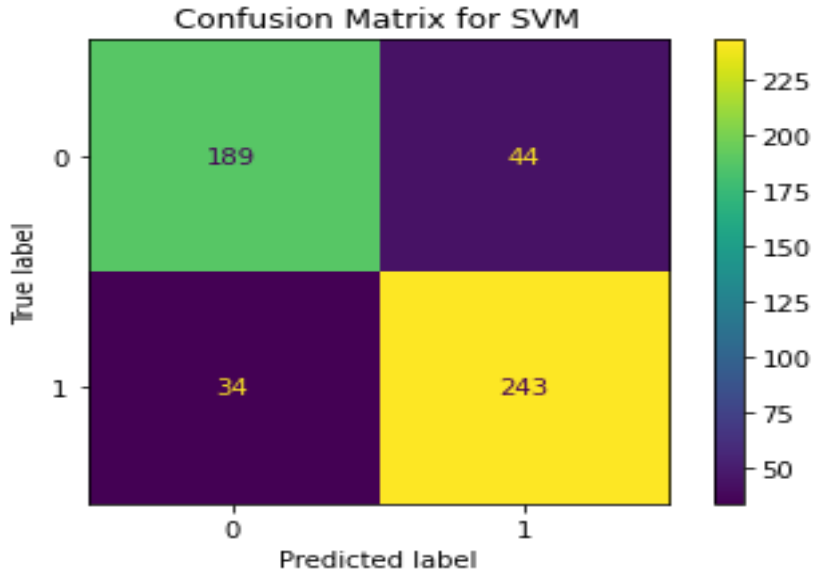
54
46
231
0
1
True label
0
1
Predicted label
225
200
175
150
125
100
75
50


Confusion Matrix for SVM
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1
Predicted label
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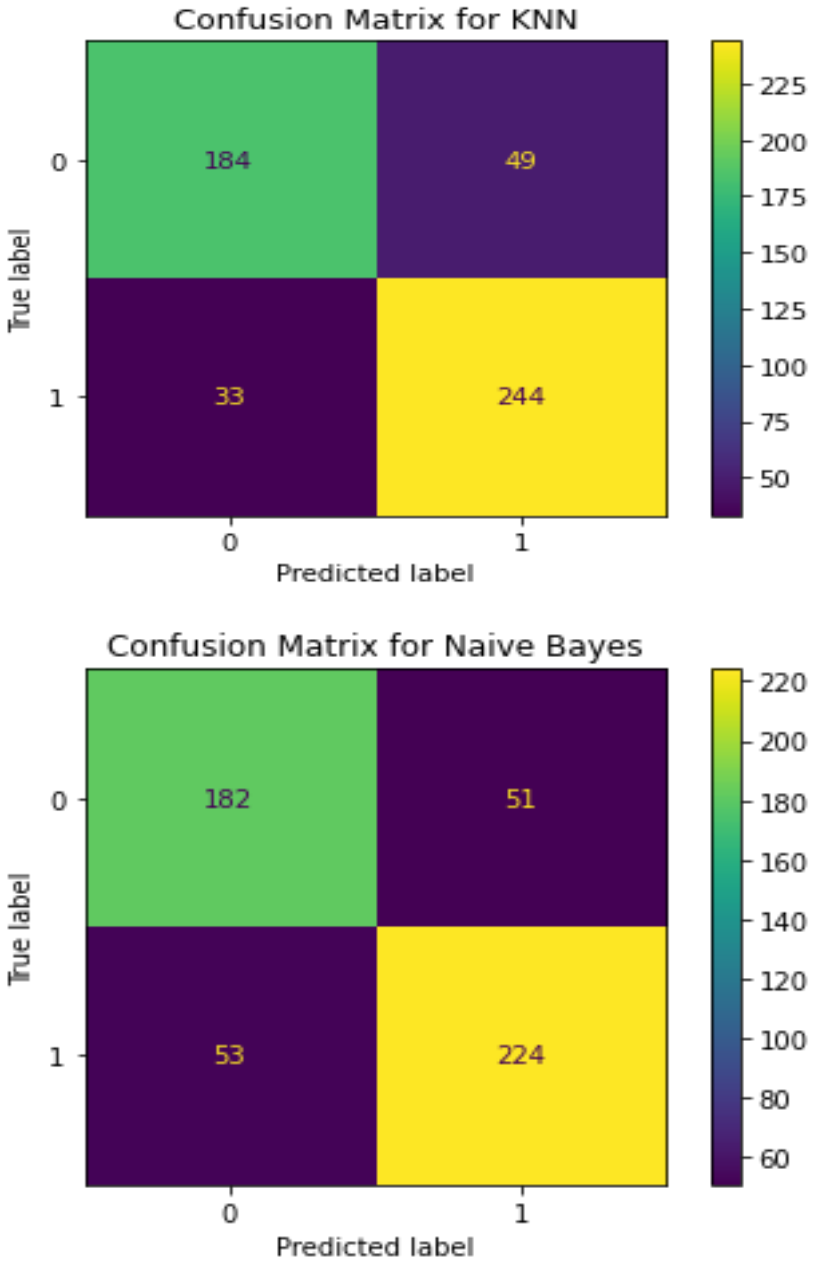
200
175
150
125
100
75
50


Confusion Matrix for KNN
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49
33
244
True label
Predicted label
0
1
225
200
175
150
125
100
75
50
Confusion Matrix for Naive Bayes
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53
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True label
Predicted label
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220
200
180
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140
120
100
80
60

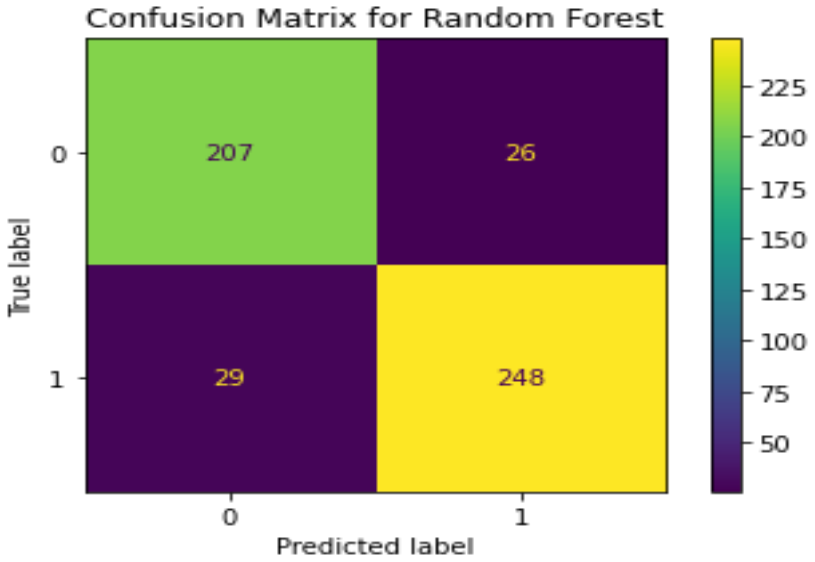

Figure 6 confusion matrices for all models

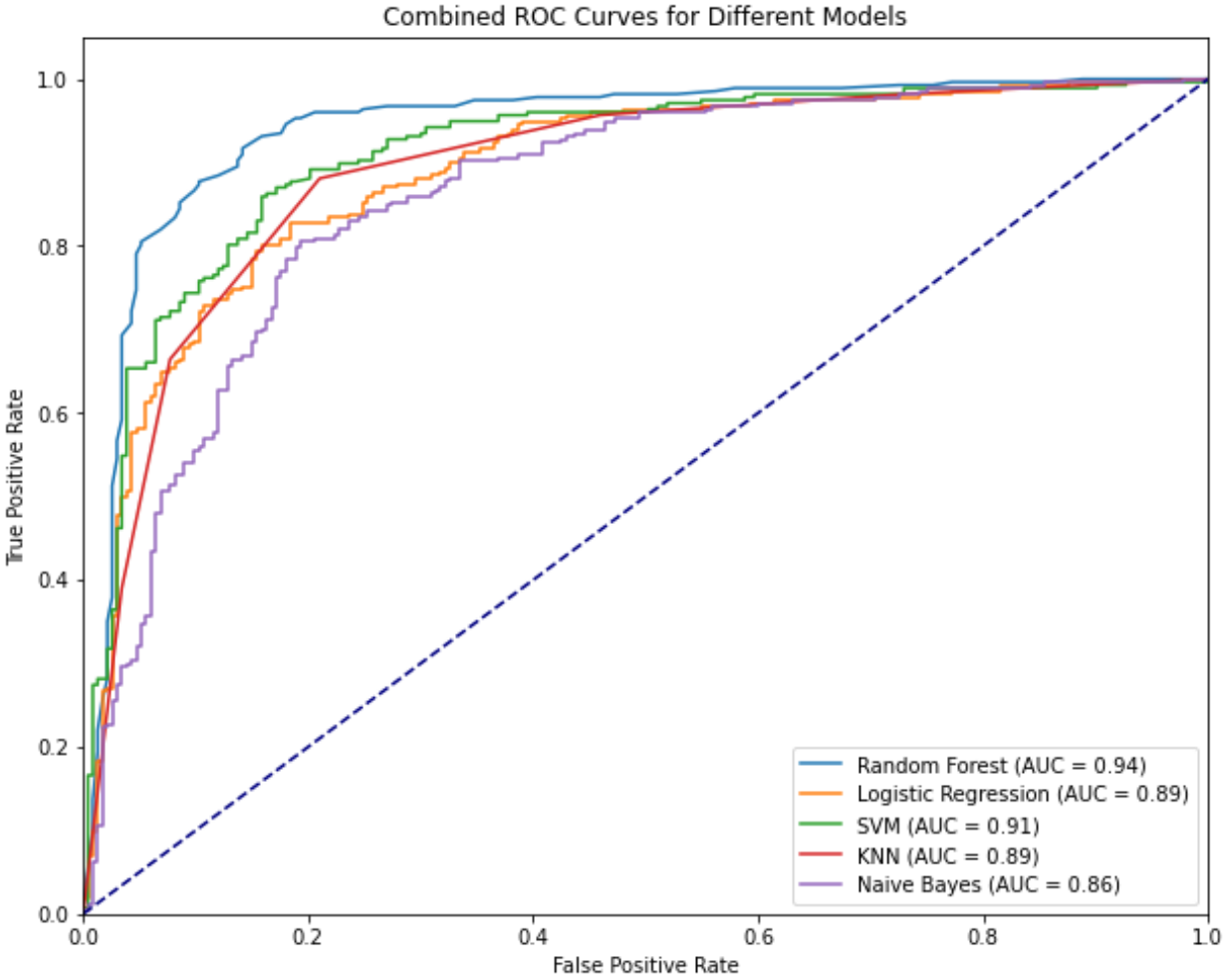

Figure 7 ROC Curve for all fuzzy based machine learning models

5. Results

The performance evaluation of Naïve Bayes, K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Logistic Regression, and Random Forest across key metrics shows varying strengths. Figure 5 shows the variable importance of the best model. Naive Bayes and Random Forest lead with the highest accuracy at 0.892 (CIs: 0.865-0.919 for Naïve Bayes, 0.834-0.920 for Random Forest), strong sensitivity (Naïve Bayes: 0.896, Random Forest: 0.877), and high F1 scores (Naïve Bayes: 0.9, Random Forest: 0.883). Random Forest achieved the best specificity (0.905) and MCC (0.78), indicating its robustness in minimizing false positives. KNN shows decent accuracy (0.839) and sensitivity (0.881), which is suitable for cases prioritizing true positives. SVM and Logistic Regression lag in specificity and F1 scores, with Logistic Regression showing the lowest accuracy (0.804) and MCC (0.303). In summary, Random Forest and Naïve Bayes provide balanced, reliable performance, while KNN can be considered for applications focused on high sensitivity. Figure 6 and figure 7 represents the confusion matrix and roc curve of all models.

6. Conclusion

This paper suggests a neutrosophic logic-based machine learning method for figuring out the risk of chronic kidney disease (CKD) so that early detection is more accurate. Combining fuzzy logic's capability to manage uncertain data with machine learning's pattern recognition, the model effectively identifies high-risk individuals with greater precision. The interpretability of fuzzy rules offers clinicians a clearer view of risk factors, aiding in decision-making and timely intervention. The results show that this hybrid approach is more accurate at predicting CKD than traditional models. This shows that it could help with proactive healthcare strategies and improve patient outcomes by stepping in early.

7. Limitation

The limitation of this study is that neutrosophic logic is rather complex, requiring significant computational and specialized knowledge for its implementation. The effectiveness of this model also depends on the quality and completeness of input data, which can vary from one real-world healthcare setting to another. Additionally, achieving interpretability for clinical decision-making may present a challenge when compared to traditional methods.

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