Retraction

Retracted: The Emerging Role of Implementing Machine Learning in Food Recommendation for Chronic Kidney Diseases Using Correlation Analysis

Journal of Food Quality

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] S. Gupta, N. Garg, D. Sinha, B. Yadav, B. Gupta, and S. Miah, "The Emerging Role of Implementing Machine Learning in Food Recommendation for Chronic Kidney Diseases Using Correlation Analysis," *Journal of Food Quality*, vol. 2022, Article ID 7176261, 10 pages, 2022.

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Research Article

The Emerging Role of Implementing Machine Learning in Food Recommendation for Chronic Kidney Diseases Using Correlation Analysis

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Kidneys are vital organs in the human body, and their effective functioning determines life quality. Chronic kidney illness is a kind of nephrotic syndrome in which the kidneys' capacity to cope normally steadily deteriorates and remains asymptomatic for a long period as the disease progresses. An early CKD detection would help the patient recover faster and easier. Using an artificial intelligence system that can effectively aid in CKD detection in time and suggest the required food nutrition for its treatment and recovery would reap immense benefits for healthcare professionals as well as the patient. ML is a part of AI technology that has been used for effective medical development. This technology helps physicians in the accurate diagnosis of kidney disease and helps in effective treatment prediction by recommending required nutrition. The present research relates to the use of ML in proper kidney disease diagnosis and food recommendations for treatment accordingly. A correlation analysis has been done in this research to observe the strength of ML using the effective finding for renal malfunctioning and identifying the best food products that could help in its treatment and recovery. IBM SPSS version 26 has been used for this research. The correlation analysis has been done to observe the impact of eight independent variables that are age, gender, blood sugar, serum albumin, creatinine, potassium, bacteria, and pus secretion on the two dependent variables that are the risk of CKD occurrence and ML accuracy. The results have exposed that the autonomous values consist of a strong positive correlation with the dependent variable ($p < 0.005$). The statistical significance values have proved that the dependent values are statistically significant (0.001). The value of ML accuracy at a 95% confidence level has been observed at 88.85%, and the CKD occurrence value is 86.95%. The results have proved that the ML algorithm detects the risk of CKD occurrence accurately in each stage via analyzing blood sugar, creatinine, and potassium levels. The result also shows that the risk of CKD enhances with an increase in age.

1. Introduction

Chronic kidney disease is among the prominent major communal health difficulties worldwide [1]. CDC report also stated that poor lifestyle choice among individuals is the main reason for increased CKD occurrence. Each day, over 360 individuals undergo dialysis treatment, and nearly 3 of the 4 CKD patients have experienced kidney failure [2]. The disease has its widespread effect due to the fact that nearly 86% of CKD case patients do not recognize that they have CKD. The delay in diagnosis is a crucial factor in its prevalence, as it typically develops symptoms after it gets too late.

Artificial intelligence (AI) is an effective technology that can analyze large data, and due to this reason, different AI technologies are being used in the healthcare system. ML is a

type of AI technology that can analyze large amounts of patient data, which is known as "electronic health record" or EHR and "electronic medical record" or EMR. These EHRS and EMR contain a sufferer's medical knowledge as well as analyze through the ML algorithm. Studies have found that diabetes, obesity, and uncontrolled blood pressure are the main reasons for CKD. An appropriate ML algorithm is effective in detecting CKD in diabetic patients with an accuracy level of 71% [3]. This has been possible by analyzing the EHR of 68,000 diabetic patients, and the results have proved that the ML algorithm is an effective technology for proper CKD diagnosis. Studies have proven that different ML procedures such as "logistic reversion," "provision vector mechanism," "naive classifier," "random forest," and so on can diagnose CKD with a 99.75% accuracy level [4]. Neural networking is another ML algorithm that can effectively diagnose CKD in a patient from a very large data set. Chronic kidney ailments have been one of the planet's most severe public health challenges and hence need some advanced technology that can aid early prediction of severe diseases; therefore, AI technology is providing a promising platform for the early risk prediction using ML, CNN, and deep neural network techniques for the enhanced treatment strategies by aggregating the large data sets of the patient's health suffering from the multiple diseases to cater the symptoms and related parameters for the early prediction.

Neural networking also provides an accuracy level of 95% and predicts an efficient treatment methodology. Researchers have often argued against the accuracy rate of support vector machine and artificial neural network. According to the studies of Almansour and other researchers, ANN has a greater accuracy level than SVM. Their studies have proven that ANN can effectively diagnose CKD in diabetic and nondiabetic patients with an accuracy rate of 99.75%. SVM on the other side can do the same with an accuracy rate of 97.99% [5]. Therefore, it can be stated that in the era of increasing CKD rates among patients, the ML algorithm has become a reliable source for medical and healthcare professionals for accurate disease detection. According to the studies of Nishat and other researchers, the "random forest" technique of the ML algorithm has an accuracy rate of 99.76% for the early detection of CKD [6].

There are studies prevailing in the literature that signify a relationship between the food habits of a person and CKD occurrence and the role of nutrition in disease treatment, recovery, and prevention [7–9]. Therefore, nutritional chart prediction with the help of AI would be of great help for the medical professionals to regulate, monitor, and treat CKD patients. ANN in support of SVM has promised efficient therapies for CKD. The present study investigated the efficacy of ML algorithms to reliably evaluate CKD and, as a consequence, prescribed a strict diet for optimal rehabilitation and management. The paper is employing a regression analysis in seeing how accurate machine learning techniques are at detecting and preventing disease and prescribing regimens. This investigation is effective in assessing the impact of machine learning techniques just on the assessment of CKD. Therefore, in this study, researchers analyze the effectiveness of ML algorithms in the proper diagnosis of CKD and accordingly suggest a dietary plan for enhanced recovery and treatment. In this research, a correlation study has been done to observe the effectiveness of ML algorithms in early disease analysis and diet recommendation.

1.1. Organization. The structure of the paper is as follows: Section 1 provides an introduction; Section 2 reviews literature; Section 3 presents proposed methodology; Section 4 elucidates the analysis and interpretation; Section 5 presents discussion and findings; and Section 6 concludes the paper.

2. Literature Review

CKD or "chronic kidney disease" is a slowly progressive disease that often results in kidney failure. Patients with high blood pressure, obesity, and diabetes often are associated with CKD and require continuous treatment and medication. Kidney disease can be caused by poor lifestyle choices such as eating spicy and junk foods, drinking too much alcohol, and so on. CKD affects over 750 billion individuals worldwide as a result of poor lifestyle choices and other ailments. SVM and neural networks, according to Battineni and other researchers, are successful in detecting CKD associated with eating habits as per the researchers [10]. Their studies have proved that CKD is a progressive disease that can be treated on the condition that the disease has been detected early. EHR and EMR data sets are used by many researchers to analyze the rate of CKD among individuals. These data are used for ML algorithm analysis to detect the CKD level. ML algorithms analyze the CKD with variables such as precision, accuracy, and prediction. According to Zubair Hasan and Hasan, an "ensemble-based classifier" is an effective method of ML algorithm for detecting CKD in patients. Their studies have proved that the ML algorithm can detect kidney disease among patients effectively and thus is used by researchers and medical care professionals to rapidly detect CKD [11]. Early detection helps in proper treatment, and this alleviates a speedy recovery for patients. Another study has shown a smart detection of CKD with different ML classifiers. According to Elhoseny and other colleagues, the "mass-based feature assortment" and "ant optimizing colony" are two very efficient ML classifiers that can enhance the rate of early CKD detection in patients. Figure 1 shows the use of machine learning classifiers on the CKD data set.

In CKD, regulating the potassium level in the blood is important to reduce the disease progression rate. Patients with high blood pressure tend to have high levels of potassium in their blood, which affects the effective functioning of the kidney. According to Maurya and other researchers, accurate and on-time prediction is necessary for any disease for effective treatment. ML algorithm is extensively used in patients to diagnose and predict treatment methods [13]. Moreover, ML algorithms can also help in nutrient suggestions in patients with high blood pressure and CKD. Less potassium diet predictions for those patients are done with different ML algorithms. The diet chart was created after analyzing patients' EHR and EMR data [14]. By following
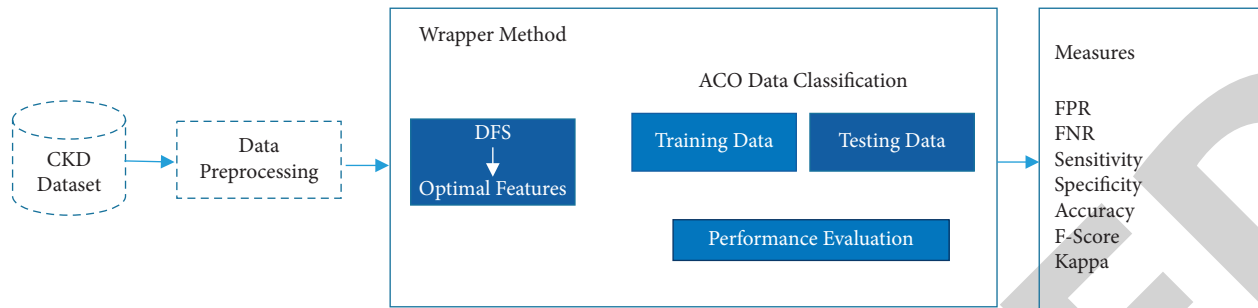
FIGURE 1: Use of ML classifiers on CKD data set [12].

this way, ML can reduce the disease progression rate among patients and can enhance the number of recovered patients.

Kidney failure is widespread in patients with CKD; CDC reports have stated that 75% of patients with CKD encounter kidney failure and require surgery. To prevent this, early detection needs to be employed that can be done with the help of ML algorithms [15]. Classification helps in the effective analysis of patient data by improving its accuracy and precision level [16]. ML algorithm helps in the detection of CKD in different levels of disease progression such as "acute kidney injury," "hypertensive crisis," "electrolyte imbalance," "fluid retention," "urinalysis," and so on [17]. The number of patients that have gone through each stage is calculated through patient EHR and EMR data to understand the percentage of individuals that had gone through the final stage of kidney failure [18]. Biopsy and dialysis are two major detection tests to accurately determine "end-stage renal disease" or kidney failure. Clinically, this stage demonstrates a phase in which only 10% to 15% of the kidneys are functioning, and the patient has a "glomerular filtration rate" of 15 to 30 ml/kg/min [19]. This stage is also associated with nausea, vomiting, extreme pain and swelling of the abdomen, fluid retention, and so on [20]. After this stage, dialysis and biopsy are done to observe the condition. ML algorithm detects a patient's kidney condition in this stage via determining the fluid retention and swelling [21]. Figure 2 shows the machine learning algorithm for CKD detection.

CKD detection is an important step to reduce the efficacy and rate of kidney failure. Researchers have used different ML algorithms to study different variables such as blood potassium count, sugar count, pus, cell count, fluid retention, and so on to analyze whether the patient has CKD or not. Classifiers can also be used in this aspect to determine the frequency of disease occurrence and the accuracy of those classifiers such as SVM and KNN in detecting CKD. According to the studies of Wang and other researchers, determining the rate of reduction of "glomerular filtration" is an effective way to determine the stage of CKD. The most typical symptoms linked with CKD were fatigue and frequent urination, "followed by difficulties of sleeping, muscle weakness, cramps and stiffness, discomfort in the bones and joints, and feeling chilly" [23]. This can be done effectively by analyzing the blood creatinine level among patients as a high level of creatinine promotes kidney functioning irregularity. High creatinine tends to reduce the level of glomerular

filtration and gradually increases fluid retention. This on the other side creates an obstacle for the body to be able to filter waste ions and fluids, and this results in poor urination levels.

Table 1 shows the gradual progression rate of CKD with respect to kidney filtration rate. From Table 1, it can be observed that as the disease progresses to a further stage, the filtration rate decreases. Thus, the fluid with waste and ions could not get filtered effectively and could not produce urine. Studies have shown that the ML algorithm can effectively detect this decreased rate of filtration and can detect the stage at which the patient has CKD. A lack of proper diagnosis is one of the major issues that has promoted the spread of CKD. According to Uhlig and other researchers, the final stages of CKD often lead to renal cancer due to mass accumulation. ML algorithm can detect this mass accumulation and can predict the probability of the occurrence of renal cancer [24]. ML algorithm is an effective technology to predict the health of the kidney in humans.

Studies have found that different ML algorithms such as random forest, SVM, and so on have an accuracy rate of over 95% and have a precision rate of over 87%. This high rate of accuracy and precision enables researchers to detect kidney health. According to the studies of Luo and other researchers, the random forest technique is effective in developing appropriate diet plans for individuals with high potassium and creatinine levels. Dialysis and kidney transplants are examples of CKD treatment treatments that raise mortality rates while also increasing public health expenses. The use of machine learning techniques to aid in the early detection of CKD in underdeveloped nations is examined in this study [25,26]. This diet was created after analyzing a patient's past medical record and demographic data. This way, doctors and medical care professionals can effectively monitor a patient's health. Deteriorating kidney function has a variety of underlying causes such as over-consumption of junk foods, smoking, alcohol consumption, genetic disorders, obesity, diabetes, and so on. These causes gradually decrease kidney functionality by lowering the rate of glomerular filtration. This paper focuses on early detection as well as analysis of the accuracy compared to the traditional approaches the present research focuses on describing the role of the ML algorithm in the effective disease diagnosis of CKD and developing appropriate dietary plans. By watching variations in blood sugar, potassium, creatinine, and pus discharge, the ML algorithm may determine
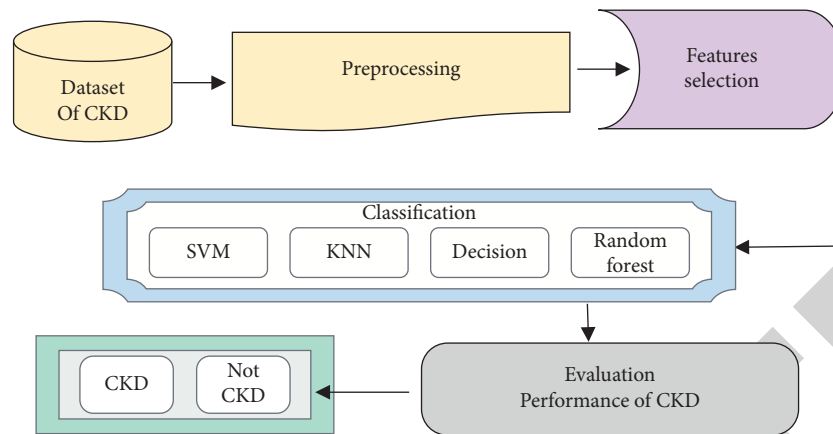
Figure 2: Role of ML algorithm for CKD detection [22].

Table 1: CKD and glomerular filtration rate.

Stages of CKD	Rate of glomerular filtration (ml/kg/min)
CKD 1	>90
CKD 2	89–60
CKD 3a	59–45
CKD 3b	44–30
CKD 4	29–15
CKD 5	<15

the CKD stage. The accuracy of the ML algorithm in detecting these alterations in a CKD patient was demonstrated in this study.

3. Research Methodology

This investigation objects to describe the role of machine knowledge algorithms in identifying CKD and generating nutritious diet plans in response. The primary research has been done by collecting patients' EHR and EMR data. The data has been collected from different diagnostic centers in the UK. This data includes the patient's clinical and demographic information such as age, sex, blood creatinine level, potassium level, sugar level, serum albumin, diabetes information, and so on. The data have been analyzed at both normal and abnormal levels. A threshold level has been set, which has been counted as the normal rate. Over the threshold rate, an abnormal rate of that substance is considered. The impact of these data levels on CKD detection by ML algorithm is analyzed.

A statistical correlation study has been done with the help of IBM SPSS software version 26. This statistical analysis helps demonstrate the correlation among the independent values as well as the dependent variable. Eight independent values were taken that are age, gender, blood creatinine, serum albumin, blood sugar, potassium, pus, secretion, and bacteria. The researchers have investigated several machine learning algorithms to examine various variables such as blood potassium count, sugar count, pus, cell count, fluid retention, and so on in order to determine whether or not a patient has CKD. In this aspect, classifiers

may be used to identify the prevalence of disease occurrence and the efficiency of classifiers such as SVM and KNN in identifying CKD. The effect of these variables was analyzed on the two dependent variables that are the risk of CKD and the accuracy of ML. The correlation analysis has been done to observe the strength at which the independent variables have influenced the dependent variable. The primary data have been collected from different doctors and medical care professionals who are associated with different healthcare sectors of the UK. The data have been collected from 20 patients who have CKD and are of the age range 40–60 (as the research focuses on CKD in adults).

Descriptive statistical analysis has been done to observe the mean, standard deviation, and so on of the dependent and independent variables. The Pearson correlation analysis has been done at a 95% confidence level. A value of +1 to −1 indicates that the independent and dependent variables are strongly correlated. Their correlation values are also determined, and the significance has been analyzed at a 95% confidence level. A value of 0.05 suggests that the values are statistically significant. The correlation study also has been performed to test whether the dependent and independent values are positively correlated or are negatively correlated.

This primary data was further analyzed with different secondary data analyses. The secondary data has been booked through different courses and papers using Google Specialist. The publications of the preceding five years, which is from 2018 to 2022, were taken. The primary data were justified with secondary research articles. Figure 3 shows the research flowchart for the research followed.

4. Analysis and Interpretation

The primary data analysis has been done by collecting EHR and EMR data from 20 individuals between the age group 40 and 60. A statistical correlation analysis has been done with IBM SPSS software.

Table 2 shows the descriptive statistical results of the dependent and independent variables. The results have shown that as age increases, the CKD occurrence enhances, and the accuracy of ML enhances. The accuracy of ML at a 95% confidence level is 88.850, and the CKD occurrence
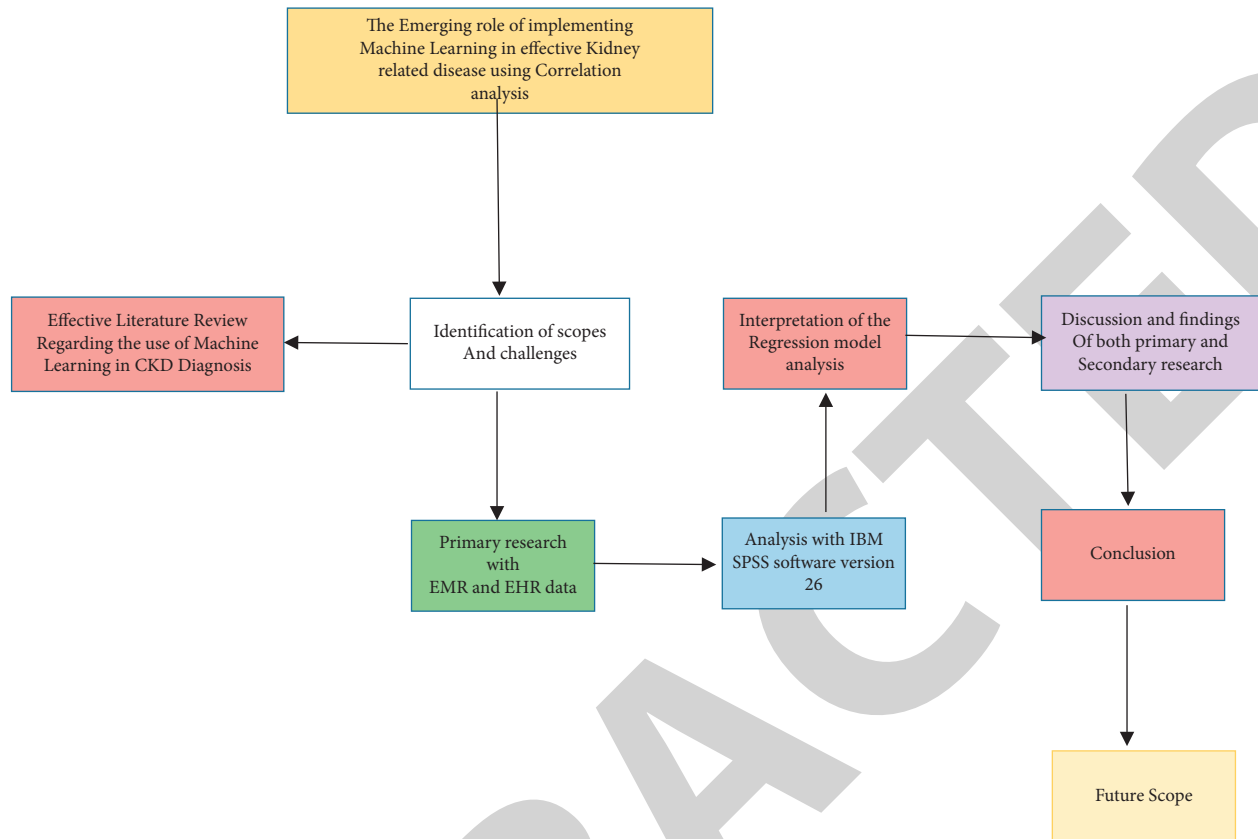
Figure 3: Research flowchart.

level is 86.950. This data shows that CKD enhances with an increase in age, creatinine, blood sugar, pus formation, and potassium and bacteria levels. However, a decrease in serum albumin levels describes kidney function abnormalities.

Table 3 shows the descriptive statistical results, and according to the data, the mean value of blood sugar is 148.50, and the standard deviation is 17.788. This indicates that the blood sugar level has deviated from its mean value by 17.788 in CKD patients. This value has the highest deviation among other variables. The risk of CKD has deviated 5.916 from its total mean value of 77.50. The accuracy of ML has deviated by 5.9161 from its mean value of 79.400.

According to the above data, it can be observed that the age variable has a positive correlation with both CKD occurrence and ML accuracy. The gender variable has a negative correlation (−0.87) with both the dependent variables. Blood creatinine has a positive correlation (0.406) with the ML accuracy and CKD occurrence; however, serum albumin has a negative correlation. The blood sugar level has a positive correlation (1.00) with both dependent variables and is statistically significant (0.001 value). The potassium level has a weak positive correlation with the dependent variables. The pus secretion and bacteria numbers have a strong positive correlation with both the CKD occurrence and ML accuracy.

Figure 4 shows the scatter plot, and it can be stated that this dependent value (risk of CKD occurrence) is statistically significant ($p < 0.001$) with independent values.

Figure 5 shows the scatter plot, and it can be stated that this dependent value (ML accuracy) is statistically significant ($p < 0.01$) with the independent values.

5. Discussion and Findings

Table 4 shows the correlation analysis between the independent and dependent variables. According to the data, age has a strong positive correlation with the increased occurrence of CKD with a value of 1.000 and has a statistical significance of 0.000. This suggests that as age increases, the probability of CKD occurrence also increases. Age also has a strong positive correlation and statistically significant values with the ML accuracy. This suggests that as the CKD occurrence rate enhances, the accuracy of ML enhances. Studies have shown that the ML algorithm has the highest accuracy level in older patients with CKD [27]. Gender has a strong negative correlation with the CKD occurrence and ML accuracy as the value was observed to be −0.87. The significance value between CKD occurrence, ML accuracy, and gender is 0.716, which suggests a strong statistical significance. According to the studies of Ricardo and other researchers, males have a higher probability of CKD occurrence than females due to the high rate of decrease in glomerular filtration [28].

The Pearson correlation value of blood creatinine has a positive correlation with the ML accuracy and CKD occurrence. The significance value is 0.075, which is higher

TABLE 2: Descriptive statistics.

		Individuals	Age	Gender	Blood creatinine	Serum albumin	Blood sugar	Potassium	Pus secretion	Bacteria	Risk of CKD	Accuracy of ML
						Statistics						
N	Valid	20	20	20	20	20	20	20	20	20	20	20
	Missing	0	0	0	0	0	0	0	0	0	0	0
Mean		10.50	49.50	1.50	2.9420	1.1385000000000000	148.50	5.1250000000000000	74.250	185.6250	77.50	79.400
Std. error of mean		1.323	1.323	0.115	0.29987	0.1008053775274390	3.969	0.3158009866632238	1.9843	4.96078	1.323	1.3229
Median		10.50	49.50	1.50	2.8500	1.2450000000000000	148.50	5.699999999999999	74.250	185.6250	77.50	79.400
Mode		1[a]	40[a]	1[a]	2.90	0.9000000000000000[a]	120[a]	5.9000000000000000	60.0[a]	150.00[a]	68[a]	69.9[a]
Std. deviation		5.916	5.916	0.513	1.34104	0.4508153443221824	17.748	1.4123049469942372	8.8741	22.18530	5.916	5.9161
Variance		35.000	35.000	0.263	1.798	0.203	315.000	1.995	78.750	492.188	35.000	35.000
Skewness		0.000	0.000	0.000	0.561	−0.454	0.000	−1.205	0.000	0.000	0.000	0.000
Std. error of skewness		0.512	0.512	0.512	0.512	0.512	0.512	0.512	0.512	0.512	0.512	0.512
Minimum		1	40	1	1.12	0.2200000000000000	120	1.9000000000000000	60.0	150.00	68	69.9
Maximum		20	59	2	5.90	2.0000000000000000	177	6.7000000000000000	88.5	221.25	87	88.9
Percentiles	95	19.95	58.95	2.00	5.8500	1.9850000000000000	176.85	6.6850000000000000	88.425	221.0625	86.95	88.850

Note. a: multiple modes exist. The smallest value is shown.

Table 3: Descriptive statistics.

| Descriptive statistics			
	Mean	Std. deviation	N
Individuals	10.50	5.916	20
Age	49.50	5.916	20
Gender	1.50	0.513	20
Blood creatinine	2.9420	1.34104	20
Serum albumin	1.138500000000000	0.450815343221824	20
Blood sugar	148.50	17.748	20
Potassium	5.125000000000000	1.412304946942372	20
Pus secretion	74.250	8.8741	20
Bacteria	185.6250	22.18530	20
Risk of CKD	77.50	5.916	20
Accuracy of ML	79.400	5.9161	20
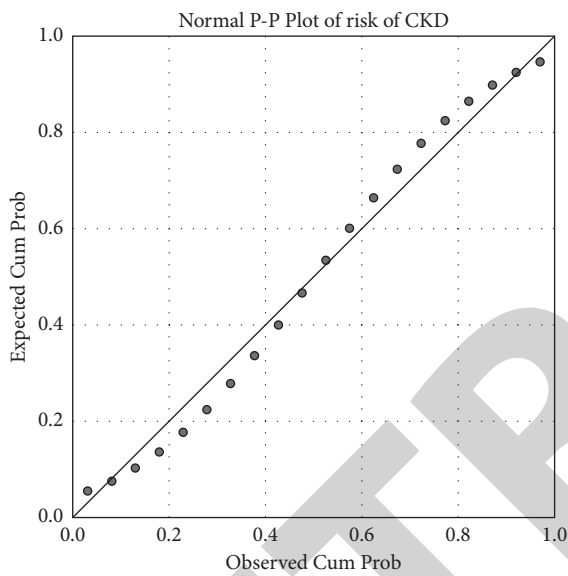
Figure 4: P–P plot of the risk of CKD occurrence.
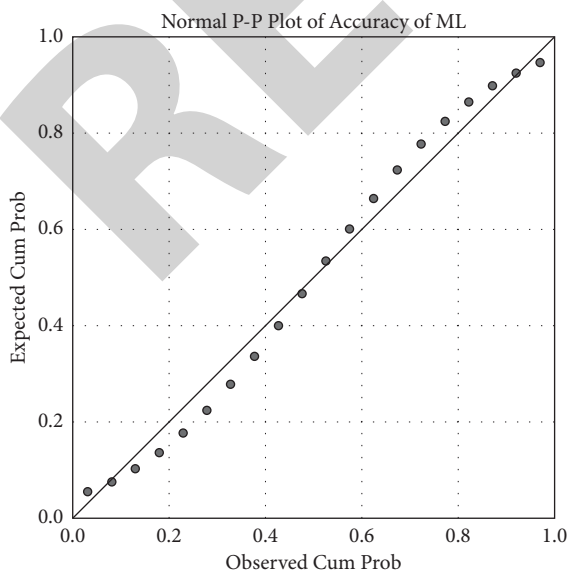
Figure 5: P–P plot of ML accuracy.

Table 4: Correlation analysis.

		Risk of CKD	Accuracy of ML
Individuals	Pearson correlation	1.000**	1.000**
	Sig. (two-tailed)	0.000	0.000
	N	20	20
Age	Pearson correlation	1.000**	1.000**
	Sig. (two-Tailed)	0.000	0.000
	N	20	20
Gender	Pearson correlation	−0.087	−0.087
	Sig. (two-Tailed)	0.716	0.716
	N	20	20
Blood creatinine	Pearson correlation	0.406	0.406
	Sig. (two-Tailed)	0.075	0.075
	N	20	20
Serum albumin	Pearson correlation	−0.089	−0.089
	Sig. (two-Tailed)	0.710	0.710
	N	20	20
Blood sugar	Pearson correlation	1.000**	1.000**
	Sig. (two-Tailed)	0.000	0.000
	N	20	20
Potassium	Pearson correlation	0.269	0.269
	Sig. (two-Tailed)	0.252	0.252
	N	20	20
Pus secretion	Pearson correlation	1.000**	1.000**
	Sig. (two-Tailed)	0.000	0.000
	N	20	20
Bacteria	Pearson correlation	1.000**	1.000**
	Sig. (two-Tailed)	0.000	0.000
	N	20	20
Risk of CKD	Pearson correlation	1	1.000**
	Sig. (two-Tailed)		0.000
	N	20	20
Accuracy of ML	Pearson correlation	1.000**	1
	Sig. (two-Tailed)	0.000	
	N	20	20

than 0.01 and reflects that blood creatinine is not statistically significant with the ML accuracy and CKD occurrence. Similar results have been found in the meta-analysis cohort study of Bach and other colleagues [29]. Their studies have proved that the level of serum creatinine is not statistically significant with CKD occurrence. This has occurred as sometimes excess creatinine can lead to kidney failure, which creates an obstacle to effective ML detection. Moreover, the Pearson correlation value has been shown to be 0.406, which indicates that creatinine level has a low statistical significance value and a weak positive correlation value with the CKD occurrence and ML accuracy.

The Pearson correlation value between serum albumin and CKD occurrence has ML accuracy is of –0.89, which indicates a negative correlation. The level of albumin protein decreases with increasing age; however, in abnormal kidney function, the album protein enhances creating albuminuria. According to the studies of Lees and other researchers, in end-stage kidney disease, the significance value has been found <0.001, which indicates a statistical correlation. However, in the primary stage, the value is > 0.001, which indicates a decrease in albuminuria [30].

The blood sugar level has a correlation value of 1.000, which suggests a positive correlation, and the significance value is 0.001, which indicates that blood sugar level is statistically significant with ML accuracy and CKD occurrence. In diabetic patients, the rate of CKD is high due to the low rate of glomerular filtration and high blood pressure. According to the studies of Krishnamurthy and other researchers, in diabetic patients, the accuracy of the CNN algorithm of ML has shown to be 89%. Their studies have shown that CKD occurrence enhances in diabetic patients [31].

The potassium level, pus secretion, and bacteria number have a positive correlation with the ML accuracy and CKD occurrence ($r = 1.000$). The statistical significance value is 0.000, which describes that these variables are statistically significant. According to the studies by Mertowska and other researchers, prolonged CKD in patients affects different metabolic pathways, especially affects urine formation. This in turn promotes bacterial growth and toxin production, which ultimately alleviates the pus secretion in the body [32]. The accuracy of the ML algorithm depends on the stage of CKD. According to Table 2, the accuracy of the ML algorithm in the detection of CKD in patients at a 95% confidence level is 88.85%, and the accuracy of CKD occurrence is 86.95%. Similar results have been observed in the research of Gupta and other colleagues. Their studies have proved that ML algorithms can effectively detect the CKD occurrence in patients with an accuracy level of 86% to 98%. Therefore, from the primary research, it can be stated that the ML algorithm is effective in detecting CKD in patients. The cumulative plot also justifies this statement as from Figures 4 and 5, it has been observed that the CKD occurrence and ML accuracy has a statistically significant relationship with the independent variables. This includes age, gender, creatinine, albumin, sugar, potassium, pus, and bacteria levels. The results have shown that ML accuracy has a significant impact on the effective detection of CKD in patients. Adult patients tend to contract CKD more frequently than younger patients due to less filtration rate of the glomerulus. As age enhances, total creatinine and serum albumin enhance due to reduced filtration rate. Moreover, improper metabolic pathways enhance the toxin storage in blood, and this produces harmful pus secretion. The results have shown that the risk of CKD occurrence enhances with the increase in pus secretion and bacterial colonization. CKD has a negative and deteriorative effect on patients' health and is associated with patient mortality. However, effective diagnosis of CKD through ML algorithm increases the probability of patient recovery. This is an effective way of improving health quality and service quality in hospitals and healthcare sectors of the United Kingdom.

6. Conclusion

The ML algorithm assists doctors and medical care providers in enhancing the recovery rate of patients by establishing an appropriate nutrition plan. ML algorithm effectively analyses the severity of CKD by determining the filtration rate of the glomerulus. The research has shown the accuracy level of the ML algorithm in the effective diagnosis of CKD, that is, 88.85%. This indicates that different ML algorithms such as CNN, naive Bayes, random forest, and so on have a high positive impact on the detection of CKD. The secondary journals have also supported this statement. Effective detection and treatment prediction of CKD via ML algorithm is necessary to reduce the mortality rate. In CKD patients, the amount of blood sugar, potassium, creatinine, and serum albumin enhances, which affects other metabolic pathways of the body. Lack of proper glomerular filtration alleviates the toxin storage and bacterial production that has been observed through pus secretion. The ML algorithm can detect the CKD stage by effectively observing the changes in blood sugar, potassium, creatinine, and pus secretion. This research has shown the accuracy of the ML algorithm in detecting these changes in a patient with CKD. The statistical significance level, the positive and negative correlation of the independent variables, indicates that the ML algorithm detects the CKD in patients more accurately and precisely and helps determine the CKD stage. There are some constraints as per the study, yet there is a virtually insufficient investigation on using the ML algorithm to detect secondary infections of persistent CKD, such as albuminuria and toxin generation.

7. Future Scope

The increasing rate of CKD has placed a large negative impact on individuals' lives. Advanced ML technology has made the early detection of CKD easier and more accurate. Doctors and medical care professionals have used ML algorithms in the effective diagnosis of CKD. However, there is very little research on the detection of secondary infections of prolonged CKD such as albuminuria and toxin production through the ML algorithm. These secondary infections also place a negative impact, especially on diabetics and patients with high blood pressure. Therefore, effective research can be done to determine the role of ML algorithms in detecting CKD-associated diseases. Further research on effective treatment prediction and nutritional chart prediction of CKD patients through ML algorithm needs to be done in the future. Advanced technologies such as CNN, ML, random forest, and different classifiers can be used for these aspects to increase the recovery rate in CKD. By following this way, researchers and medical care professionals can enhance their service quality in accurate CKD diagnosis and treatment. Effective detection of CKD through ML algorithm is rapid and cost-effective, and due to this reason, the method can gain large popularity in the future.

Data Availability

The data shall be made available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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