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Automatic kidney disease prediction using deep learning techniques

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ABSTRACT

The kidneys play an energetic role in eliminating excess products and fluids from the body, by a complex mechanism which is crucial for upholding a stable balance of body chemicals. Chronic kidney disease (CKD) is considered by an unhurried weakening in renal function that may eventually result in kidney injury or failure. The difficulty of diagnosing the illness rises as it worsens. However, using data from normal medical visits to evaluate the various phases of CKD could help with early detection and prompt care. Researchers suggest a classification strategy for CKD along with optimization strategies used in the learning process. The incorporation of artificial intelligence offers promise because it may often astonish with its skills and enable seemingly difficult undertakings. Modern machine learning techniques have been developed to detect renal illness in light of this. In the current study, a new deep learning model for CKD initial recognition and prediction is introduced. The main objective of the project is to build a strong deep neural network (DNN) and estimate its result outcomes in comparison to other leading-edge machine learning techniques. The outcomes demonstrate that the proposed strategy outperforms current approaches and has promise as a useful tool for CKD detection.

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1. INTRODUCTION

Patients who have chronic renal disease (CNR) see a steady decline in kidney function. It poses a serious threat to global public health, and early detection is essential to enabling effective responses. For the entire populace as well as in particular for high-risk groups such those with diabetes, hypertension, and particular ethnic backgrounds, routine screening is advocated. Currently, glomerular filtration rate (GFR) estimation and urine protein or albumin assays are used to screen for CNR [1]. However, despite high income levels and at-risk populations, low screening adherence continues, primarily as a result of the requirement to collect serum or urine samples. Unfortunately, the majority of renal failure affected persons in small and middle income based countries still have restricted entree to life-saving actions like dialysis and kidney

transplantations. This problem is especially troubling because developing countries like China and India are predicted to experience an unanticipated rise in the number of renal failure cases [2]. Chronic renal failure makes it difficult for the body to properly eliminate extra fluids, electrolytes, and wastes, which can result in harmful accumulations. When it is more advanced, issues like high BP, anemia, injured bones, and nerve hurt may result. To improve the quality of life of patients and the health of the world's kidneys, a thorough approach to this problem is needed [3].

The kidney function gradually deteriorates over months or even years with congenital kidney disease (CKD). As patients with end-stage renal disease (ESRD) can preserve their health with treatments like hemodialysis, peritoneal dialysis, or kidney transplantation, early detection of CKD is essential for minimizing the burden on medical resources. Blood testing, which involves determining the blood urea nitrogen (BUN) index and creatinine levels, is frequently used to make an early diagnosis of CKD. Artificial intelligence (AI) systems have recently become effective tools for aiding in the diagnosis of diseases [4]. Particularly with machine learning, existing data can be intelligently interpreted, creating useful knowledge and enhancing the effectiveness of the diagnostic procedure. This method has already demonstrated success in evaluating the health of the human body, looking at risk factors for diseases, and diagnosing numerous ailments. Researchers have looked into using supervised algorithms to identify chronic kidney illness, including random forest, fuzzy C-means (FCM), Naive Bayes (NB), support vector machine (SVM), gradient boosting (GB), and regression based classifiers. Machine learning is used to improve the quality of medical data, decrease hospital admissions, and eventually lower medical costs [5].

As a result, compared to more traditional methods, these models are applied more frequently in diagnostic analytical research. Only proper treatment and early detection of chronic diseases (CD) can lower their mortality rates. The feature abstraction and catecorization steps in conventional machine learning rely on two different approaches, which results in laborious calculations. The conventional method is therefore no longer appropriate for real-time diagnostic applications.

Contrarily, neural networks (NN) frequently outperform conventional machine learning methods, and the performance of the resource learning architecture can be further improved. NN models have already been used to identify kidney diseases, although the bulk of CKD models currently on the market have poor classification accurateness. As a outcome, this work presents a novel CKD model that uses deep learning to make predictions. The Figure 1 shows the different stages of CKD.

This paper's primary contributions are:

- The detection and diagnosis of CKD have been proposed using deep neural networks (DNN).
- The suggested model's computational precision is contrasted with that of other published classification techniques.
- Additionally, the performance is assessed using a variety of performance metrics.

The breakdown of the paper's structure is as follows: section 1 contains an introduction to the CKD. In section 2, the related works on machine learning methods in the CKD field are presented. The deep neural model for CKD early detection is presented in section 3. In section 4, the findings are covered in detail along with an explanation. Section 5 summarizes the results and casts an eye towards the future.

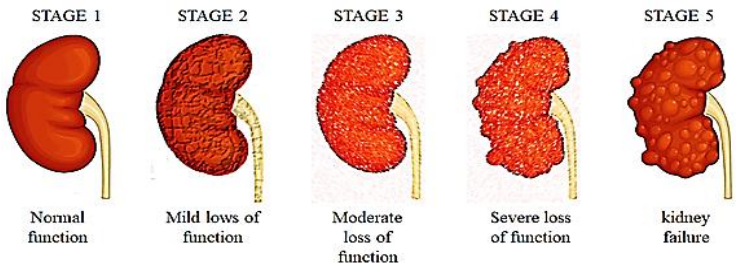

Figure 1. Different stages of CKD

2. LITRATURE REVIEW

Effective management and treatment of CNR are thought to depend greatly on early detection and characterization of the condition. This is done by using effective data mining techniques to unearth and extract hidden information from clinical and laboratory patient records. The information that emerges may help physicians correctly classify the stages of illness severity. Elkholy *et al.* [6] suggested the modified deep belief network architecture for CKD prediction, since to improve clinical analysis of the CKD patient's report. The planned is one of the intelligent and advanced models, which use the SoftMax as the activation

function at classification layer and categorical cross-entropy as error function. The author produced 98.5% accuracy. This model gave best accuracy rate than the previous models. Johari *et al.* [7] introduced a novel prediction algorithms two-class decision forest and NN to guess the possibilities of affected person who hurts from chronic case of kidney diseases. Among these two models, Decision Forest gave the best performance than the two-fold NN. This paper also compared the proposed work with some other machine learning algorithms such as k-nearest neighbor (KNN) and SVM.

Ghafar *et al.* [8] planned to use SVM algorithm for CKD prediction. The analysis of the planned model is done on the IBM SPSS statistic. In this research, the advanced feature selection improved the accuracy rate to 93.5%, which model hold the 50% validation. This model predicts the stages of the Rubia and Lincy [9] used two various shape NN, which is combined with PCA to detect the CKD. Generally early diagnosis of CKD is difficult. So the author suggested this automatic detection method for early diagnosis of CKD. Also, this paper used some other machine learning algorithms such as clustering algorithm, Naïve Bayes and decision tree algorithms. Yashfi *et al.* [10] suggested random forest and artificial neural network (ANN) technique for CKD detection on the UCI Machine learning Repository. The researcher considered 455 patient's details for the training purpose. The planned model generated 97.12% and 94.5% accuracy for random forest and ANN technique respectively.

Bhowmick and Xavier [11] recommended KNN based algorithm for CKD prediction with UCI dataset. This model is compared with decision tree and ad boost algorithms. The planned KNN based model produce the 98.2% accuracy rate. Rajeshwari and Yogish [12] advised a novel NB algorithm for CKD detection. The system compared with other technologies like SVM, random forest, and decision tree. From the experimental result, the proposed model achieved best accuracy rate with 98.75%. It helps the doctor for automatic kidney disease detection. Islam and Ripon [13] used AdaBoost and Logit Boost for CKD. The main objectives of this research is verifying the outcome of the boosting algorithm and finding the relation between attributes of the CKD detection. The author combined the data mining techniques with boosting algorithm for best result. Vishwanatha *et al.* [14] discussed the problems related to CKD. Damodara and Thakur [15] considered adaptive fuzzy logic for CKD. This analysis the stages of the CKD. Table 1 mentioned the various works related to CKD prediction.

Table 1. Literature analysis of the diagnosis of chronic diseases

Reference	Model	Accuracy
[16]	Neural network classifier	95%
[17]	Logistic regression, decision tree	93%
[18]	XGBoost	95.8%
[19]	SVM	95.8%
[20]	SoftMax regression	96%
[21]	KNN, SVM	93%
[22]	SVM	96.1%

Vijayalakshmi and Sumalatha [23] recommended machine algorithms for CKD prediction. The paper analyzed various research paper related to the CKD. CRD, also known as CKD, is a disorder in which the kidneys are unable to perform as they should, impairing their capacity to filter the blood in a manner similar to that of healthy kidneys. Unfortunately, when this common disease reaches its terminal stages, there is no known cure, leaving patients with little choice but to rely on dialysis or kidney transplantation, both of which may be time-consuming and expensive procedures. Machine learning approaches are being used to diagnose the condition early on to overcome these issues. Four machine learning algorithms-SVM, KNN, random forest algorithm, and decision tree algorithm-are used in the paper [24] cited above. The UCI repository is where the dataset for these algorithms' training is taken from. Maurya *et al.* [25] also discussed about the CKD prediction.

3. PROPOSED MODEL

It is critical to get a kidney disease diagnosis early on so that patients can avoid significant problems. It takes careful research to understand the elements that contribute to renal disorders. Today's healthcare industry relies heavily on AI to extract insightful information from health data while maintaining privacy. In healthcare organisations, deep learning and notably classification plays a crucial role. Each dataset's target category is determined through the classification process, which also provides a useful tool for making classifier suggestions that may successfully handle novel cases. The use of deep learning techniques to automate the extraction and interpretation of functions, producing high-performing models, has

recently increased in the field of kidney disease. A subtype of machine learning called “deep learning” places a strong emphasis on learning and building several hierarchical layers.

A DNN is a kind of neural network that has numerous layers of nodes, enabling it to recognise and process data via various stages between input and output. In the area of kidney disease diagnosis and analysis, deep learning models can produce outstanding outcomes because to this hierarchical approach. Deep learning does, in fact, rely on computational models with numerous layers that are capable of capturing data structures at different degrees of abstraction. Learning features in hierarchical structures, where higher-level characteristics are produced by mixing lower-level features, is the main goal of deep learning systems. Convolutional neural networks (CNN) will be used in the context of the suggested model for predicting CKD. CNNs have demonstrated promising outcomes in medical diagnostics, including the prediction of CKD, and are particularly well suited for picture and pattern recognition tasks. The work flow of the proposed model shown in Figure 2.

Data gathering is the first phase in our research technique, which also includes pre-processing, feature engineering based on deep learning, classification, and evaluation. Our proposed model is based on the UCI Dataset, which consists of 25 attributes, including 14 nominal, 11 numerical, and 1 class attribute. These attributes collectively represent data from 400 patients, including 250 cases of CKD and 150 cases of non-CKD. The next phase, known as pre-processing, includes solving the missing value issue. This work estimate missing data and employ strategies to get rid of noise, such as outliers. Additionally, as part of the pre-processing stage, this proposed algorithm undertake normalisation and evaluate the handling of unbalanced data. The dataset description is mentioned in Table 2.

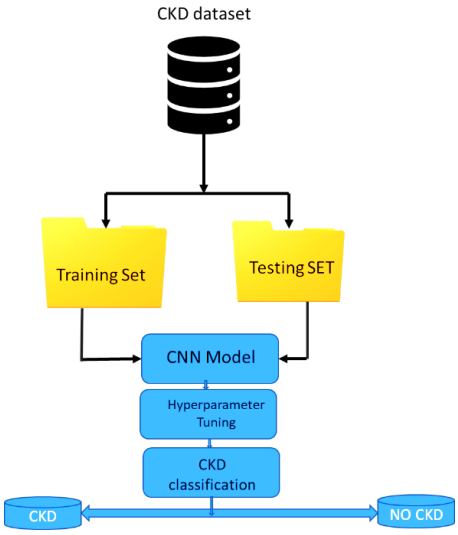

Figure 2. Work flow of proposed work

Table 2. Dataset description

Specification	Features	Value
Age (in years)	AGE	0–90
Coronary artery disease	CAD	Yes, No
Bacteria	BA	Existing, not existing
Blood glucose (BG)	BGR	0–490
Blood pressure	BP	0–180
Hemoglobin	HEMO	0–17.8
Anemia	ANE	Yes, No
Class	CLASS	Not CKD, CKD
Diabetes mellitus	DM	Yes, No
Hypertension	HTN	Yes, No

It is likely that some measurements during the patient evaluation will be missing or insufficient. 158 of the cases in the data collection are entirely finished, and the remaining instances contain some incomplete data. Ignoring the incomplete records is a simple strategy for dealing with these missing values, however this approach is impracticable for small datasets. In order to find any attributes with missing values, the data set is carefully inspected throughout the data preparation stage. Mean imputation, a statistical approach, is used to

estimate the missing values to address the absence of numerical features. On the other hand, the mode approach is used to substitute the missing values for nominal features. Given that most deep learning algorithms only accept numeric inputs, categorical values need to be encoded into numerical representations. The binary numbers "0" and "1" are used to indicate category traits like "no" and "yes". To ensure that no one variable dominates the others, data transformation entails transforming numbers to the same scale. This stop learning algorithms from interpreting larger values-regardless of their real weight or significance-as greater and smaller values-as lower. Data transformation seeks to alter dataset values in order to improve their suitability for subsequent processing. A data normalisation technique is used in this study to improve the precision of machine learning models. The data are scaled throughout this normalisation procedure between -1 and +1. As a result, the translated data will be standardised with a standard deviation of 1 and a mean of 0. The pre-processed data is then split into distinct training and testing sets. The chosen CNN model is subsequently trained using the training data. One of the most well-liked DNN, particularly in the context of computer vision applications, is CNNs or ConvNets. These networks are created primarily to analyse visual imagery. Contrary to conventional NN, which mostly depend on matrix multiplications, CNNs use a unique method called "convolution". Convolution in mathematics is a mathematical operation that is used to two functions to produce a third function that explains how the shape of one function is changed by the other. The convolution procedure in the context of CNNs entails applying a filter (sometimes referred to as a kernel) over the input image to identify different features and patterns.

This filter moves across the full input and multiplies elements-by-elements with the matching pixels of the image at each place. The results are then used to create feature maps that draw attention to particular patterns or information in the image. CNNs are particularly efficient in tasks like object recognition, image classification, and object detection in computer vision applications because they can automatically learn significant characteristics and patterns from the input. The CNN architecture is shown in Figure 3.

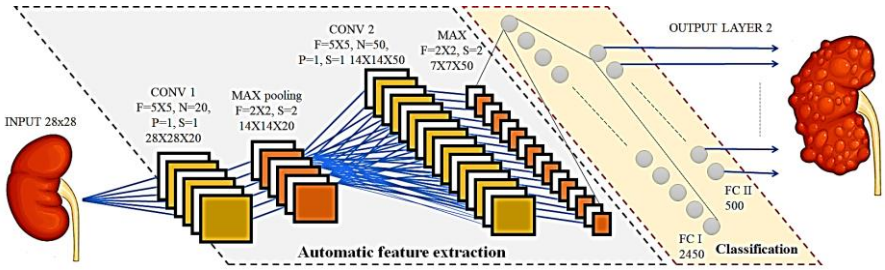

Figure 3. CNN for CKD prediction

4. EXPERIMENTAL SETUP AND RESULT ANALYSIS

Pre-processing, system hyper parameter-tuning, and ccategorization are the three primary components of the suggested model. Preprocessing is one of these stages that is particularly important since the database could comprehend noise and redundant standards. The management of absent values, categorical based data encoding, data conversion, outlier and extreme value removal, and feature selection are just a few of the techniques used in this phase. The CKD data set is pre-processed and then divided into training and testing data sets in order to properly prepare it. Only a few features are kept in this preparation, and the treated data is then sent for additional processing. A CNN model is used for model training. However, there are a number of hyperparameters in this CNN model that need to be optimised. A time-consuming and difficult experimental process is choosing the best hyperparameters. The Adam optimizer is used to tackle this optimisation problem. During the training phase, the Adam optimizer initialises hyperparameters with reduced parameter values, improving the effectiveness and efficiency of the optimisation process. The hyper parameter setting is given in Table 3.

Table 3. Hyper parameter setting

Hyper-parameter	Setting
Epochs	500
Batch size	30
Dropout rate	0.5
Activation	ReLU
Activation function at output layer	SoftMax
Optimizer type	Adam
Loss type	Cross-entropy

Some of the dataset description is displayed in Figure 4. The dataset is evenly distributed, guaranteeing flawless accuracy-the main metric on which all classifiers rely. The percentage of cases that were correctly categorised is known as accuracy. The advantages of utilising CNNs allow the suggested model to attain excellent accuracy. The model is pre-trained by CNN, which enables it to identify local optimum and weighting components in a single step. This method reduces training time by efficiently addressing underfitting concerns and fine-tuning the entire deep model in only one iteration.

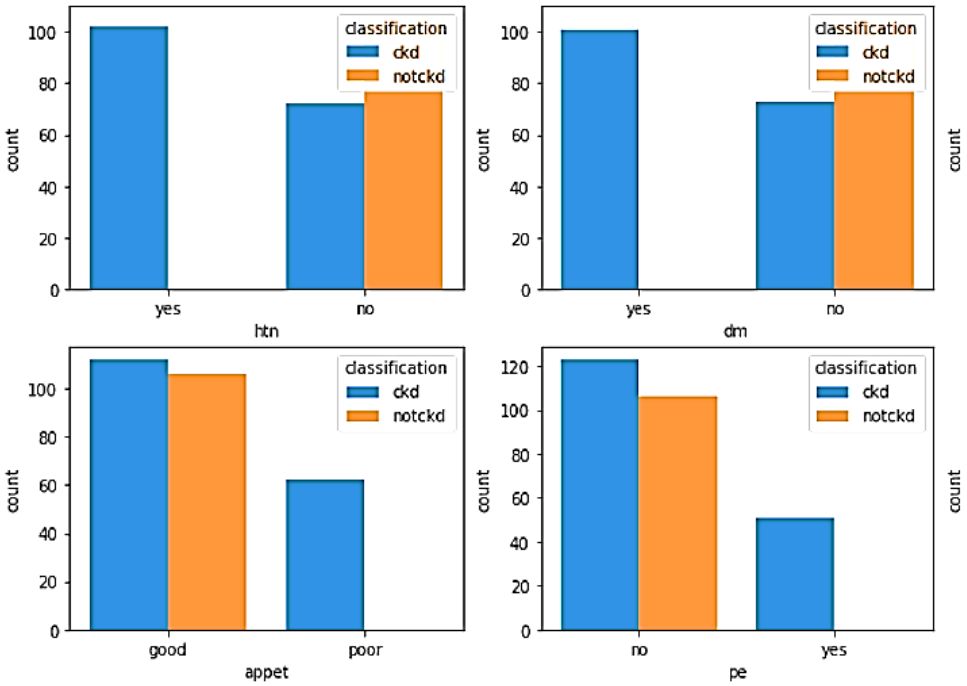

Figure 4. Dataset description

The training and validation are displayed in the Figure 5. The performances like precision, recall, accuracy, F1-score are analysed very deeply, and presented in the Table 4. Precision and recall are crucial for information retrieval, with the positive class receiving more weight than the negative class. The proportion of correctly predicted positive outcomes is shown by the accuracy value, which ranges from 0 to 1. It gauges how well forecasts turn out. The percentage of cases that are actually positive and are correctly classified as such is known as the true positive rate (TPR), often referred to as recall. The proportion of all positives that are anticipated to be positive is the same. The F1-score, which efficiently balances both precision and recall, is the harmonic mean of both. It can be used to assess model performance on unbalanced datasets because it accounts for both false positives and false negatives. The proposed model achieved the 97% accuracy rate with minimum loss function.

From the result analysis some of the some of the outcomes are observed. Red blood cell (RBC) levels that are normal suggest a lower risk of CKD. On the other hand, abnormal RBC counts can dramatically raise the risk of CKD. Pus cell, Pus cell clump, and bacteria all exhibit comparable patterns. If the Pus cells are normal, there is a nearly equal risk of having CKD or not. On the other hand, Pus cell aggregates, bacteria, and atypical Pus cells all point to the presence of CKD. Pus cell clumps, bacteria, and aberrant Pus cells can all be thought of as reliable indicators of the existence of CKD. CKD is linked to the presence of diseases such hypertension (HTN), diabetes (DM), coronary artery disease (CAD), swollen feet (PE), anaemia, and poor appetite. However, CKD can develop even in the absence of hypertension. According to the analysis presented above, it is clear that even just one of the conditions listed above - abnormal red blood cell count, bacteria, hypertension, pus cells, diabetes, coronary artery disease, lack of appetite, anaemia, or swollen body parts - significantly raises the risk of developing CKD.

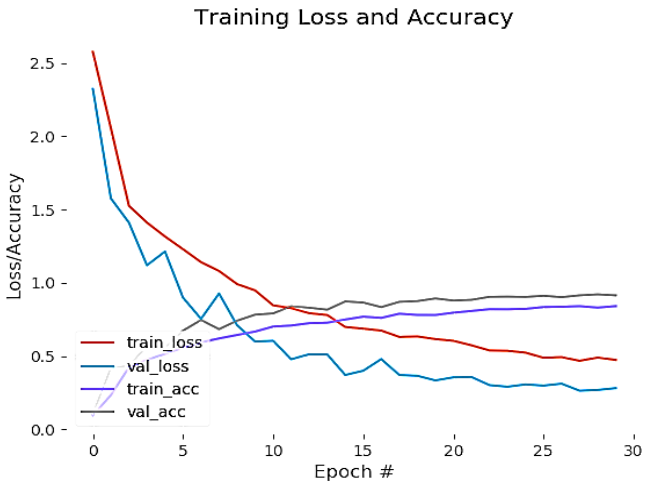

Figure 5. Accuracy and loss function

Table 4. Performance analysis

	Precision	Recall	F1-score	Support
0	0.97	0.98	0.96	72
1	0.98	0.95	0.95	48
Accuracy			0.97	120
macro avg	0.97	0.96	0.98	120
weighted avg	0.97	0.97	0.98	120

5. CONCLUSION

The main causes of CKD, include excessive blood pressure and diabetes. GFR and kidney injury indicators are used by investigators around the world to recognize CKD, a disorder that causes deteriorating renal function over time. Unfortunately, premature mortality is more common in people with CKD. For doctors to stop the course of CKD, early diagnosis of the different disorders connected to it is difficult. Researchers tested solutions to this problem and restored missing values in the database by averaging related attributes. They then performed numerous attempts to adjust the NN parameters until they found the ideal values. Significant indicators for predicting CKD include key characteristics like hemoglobin, red blood cell count, specific gravity, packed cell volume, serum creatinine, albumin, and hypertension. Deep learning models were applied for categorization using these chosen features. The proposed deep neural model demonstrated good outcomes in CKD prediction, outperforming other conventional machine learning techniques.

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