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Original Article

Synergistic Excellence: CNN- LSTM Hybrid Model for Improved CKD Diagnosis

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Abstract *- Chronic Kidney Disease (CKD) is a widespread and potentially fatal ailment that impacts millions of individuals globally. Early detection and timely intervention play a crucial role in preventing disease progression and improving patient outcomes. In recent years, advancement in Machine Learning (ML) and data analytics has shown promising potential for aiding the diagnosis and management of diseases. This study investigates the utilization of the CNN LSTM hybrid model to detect CKD using CSV data. To ensure the study's efficiency, the dataset is collected from the Kaggle repository. The dataset contains 400 samples with 37 different attributes for each sample. The prepared data is utilized for the prediction process, where a CNN is employed. The LSTM network used in this model analyzed the temporal dependencies and patterns in sequential data. The performance of the model was assessed using different performance metrics, resulting in an impressive accuracy rate of 98.75%. The results of this paper carry substantial significance in the progression of Deep Learning (DL) oriented diagnostic instruments for the prompt detection and management of CKD.*

Keywords *- Long Short-Term Memory networks, Deep Learning, Kidney function, Machine Learning, Chronic Kidney Disease.*

1. Introduction

Kidneys are vital organs responsible for various crucial functions in the body. It performs the filtration of waste products and surplus compounds from the bloodstream, manages the equilibrium of fluids and electrolytes, upholds the body's acid-base balance [1], and generates hormones responsible for blood pressure regulation [2]. The outer region of the kidney is known as the renal cortex [3]. It contains millions of tiny filtering units called nephrons [4], which are responsible for the kidney's primary function - filtering the blood to remove waste products, excess substances, and toxins.

The inner section of the kidney, known as the renal medulla, has a vital function in concentrating urine by absorbing water and retaining it in the body, which is essential for maintaining proper hydration and conserving water in times of fluid scarcity [5]. In Figure 1, both normal and CKD images are depicted side by side for comparison. The renal pelvis serves as the central collection area within the kidney, where urine from multiple nephrons is accumulated. However, the kidneys are susceptible to various diseases, with the major one being CKD, where kidney function gradually deteriorates over time, often due to conditions like diabetes and hypertension [6]. It is a progressive and irreversible condition that can lead to kidney damage and a decline in kidney function. CKD is often asymptomatic in its early stages, which makes it challenging to detect without proper screening and testing.

Marked by a sudden and severe drop in kidney function, Acute Kidney Injury (AKI) is a notable condition often brought about by infections, dehydration [7], or specific medications. Other major kidney diseases include kidney stones [8], Polycystic Kidney Disease (PKD) [9], glomerulonephritis, and kidney cancer. These diseases can have severe consequences for overall health and may require early detection and appropriate medical intervention to manage effectively.

CKD is commonly categorized into various stages according to the estimated Glomerular Filtration Rate (eGFR) [10], which reflects the kidneys' blood filtering rate. The stages range from Stage 1 to Stage 5. Diabetes, hypertension, glomerulonephritis, and polycystic kidney disease are among the common factors leading to CKD. Early stages of CKD may be asymptomatic or present with mild symptoms, such as fatigue, frequent urination, and swollen ankles [11]. As the disease progresses, more severe symptoms can occur, including nausea, loss of appetite, difficulty concentrating, and changes in urine output. Additionally, CKD increases the risk of other complications, such as cardiovascular disease, anaemia, and bone disorders. Figure 2 illustrates the different stages of CKD based on eGFR levels.

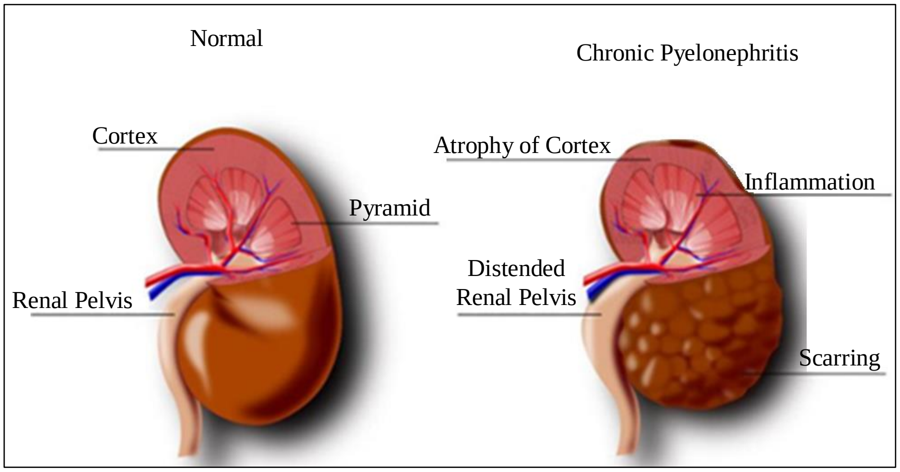

Fig. 1 Normal and CKD image

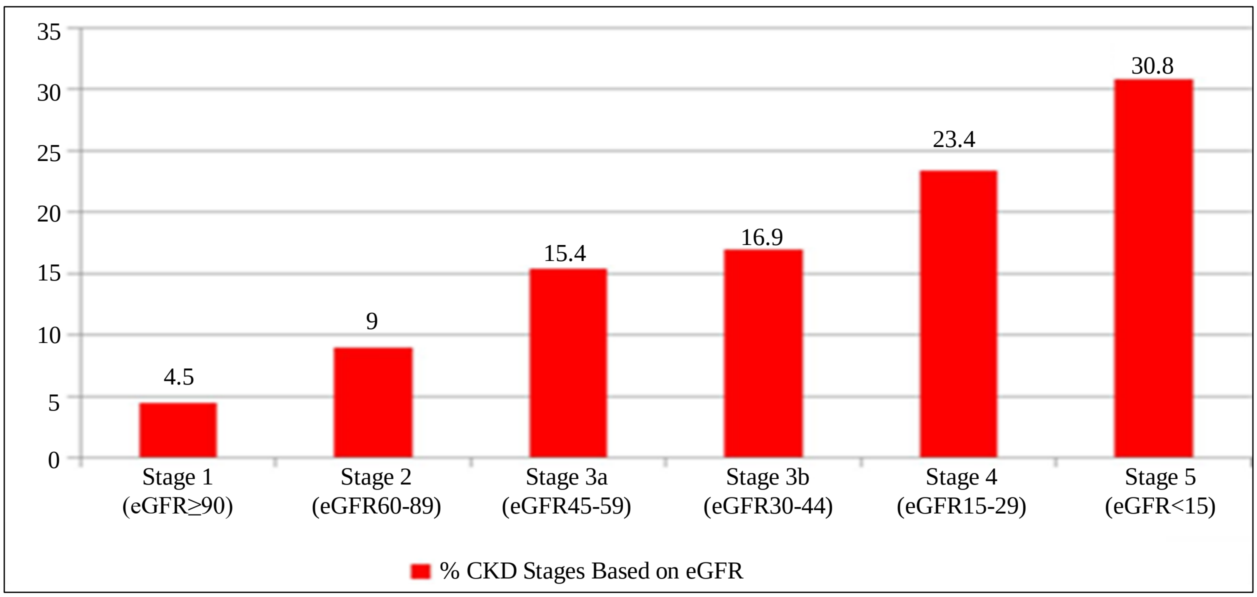

Fig. 2 CKD stages based on eGFR

Diagnosis of CKD involves assessing kidney function through blood tests and urine tests to detect abnormal levels of creatinine, Blood Urea Nitrogen (BUN), and protein in the urine [12]. Imaging studies like ultrasound or CT scans [13] can help identify kidney abnormalities.

The objectives of treatment include decelerating CKD advancement, handling symptoms, and averting complications. Lifestyle modifications, such as dietary changes and blood pressure control, are essential components of CKD management. Kidney transplantation or dialysis might become essential in later stages to restore kidney function [14].

Early detection allows for better management of underlying conditions, like diabetes and hypertension, which are often associated with CKD [15]. By identifying CKD at an early stage, healthcare providers can implement measures to preserve kidney function, enhance the patient's quality of life, and reduce the burden on healthcare systems by minimizing the need for costly and intensive treatments like dialysis or kidney transplantation [16]. Regular check-ups and adherence to medical advice are essential for individuals at risk or diagnosed with CKD.

Challenges in traditional prediction methods for CKD include limited data features that may not fully capture the complexities of the disease, difficulty in handling non-linearity and interactions among variables affecting CKD progression, and issues related to managing missing data effectively [12]. These limitations can lead to less accurate predictions and hinder the ability to identify high-risk individuals early, potentially impacting timely interventions and personalized treatment strategies for better patient outcomes. Accurate prediction models of CKD are essential to enable early identification of high-risk individuals, facilitating timely interventions and personalized treatment [17] plans.

By identifying those at risk, healthcare providers can implement preventive measures and allocate resources more efficiently, reducing disease progression and potentially alleviating the burden on healthcare systems. These models play a crucial role in promoting proactive management of CKD, enhancing patient quality of life, and potentially reducing healthcare costs associated with advanced stages of the disease. The combination of CNN and LSTM networks [18] holds excellent potential for predicting CKD due to their complementary strengths. CNNs excel at extracting spatial features from medical images, providing valuable information about the kidney's structure and morphology.

On the other hand, LSTM networks are proficient in capturing temporal dependencies and patterns in time-series data, like longitudinal patient records. Through the fusion of these two architectures, the model can skillfully harness spatial and temporal information, facilitating a more holistic grasp of the intricate progression of CKD. This fusion enhances predictive accuracy, facilitates early identification of at-risk individuals and leads to improved CKD management and patient outcomes. While previous research has shown that integrating different neural network architectures can be effective, more thorough studies are required to examine the possible advantages of integrating not only different deep learning models but also taking non-neural network techniques into account.

Furthermore, there is little investigation of interpretability and explainability features in the context of CKD detection, and there is disagreement on the best combination of tactics and ensemble sizes. By filling in these research gaps, ensemble models for chronic kidney disease diagnosis could become more reliable and accurate, and they could also be easier to understand. The significant contribution of this research work includes:

- A novel deep learning-based hybrid model for the detection of CKD.
- Performance evaluation and comparison of the proposed method with existing methods.

2. Literature Review

Ma et al. [19] introduced a method for detecting, segmenting, and diagnosing chronic renal failure within the context of the Internet of Medical Things (IoMT) platform. Moreover, the proposed approach combines elements of SVM and MLP with the Backpropagation (BP) algorithm. The primary data input for the algorithm is an ultrasound image, which undergoes preprocessing, followed by the segmentation of the kidney region of interest within the ultrasound image. The method is computationally intensive and requires powerful hardware resources, such as GPUs or TPUs, for efficient training and inference.

A popular deep-learning CNN architecture is employed by Cruz et al. [20] to automatically identify and select the appropriate range of slices within the CT images that encompass the kidneys, facilitating the subsequent kidney segmentation process. KiTS19 database with CT images was acquired to carry out the experiments. The selection of slices containing kidneys to be segmented was accomplished using the AlexNet network, as employed by the authors. The use of AlexNet in this context presents a challenge due to its deep architecture, which demands a substantial amount of memory. This memory requirement can become a limitation, mainly when dealing with large datasets or resource-constrained computing environments. A significant drawback of this study is the lack of consistent, measurable enhancement in kidney segmentation resulting from the steps aimed at scope reduction and false positive reduction.

The approach introduced by Kriplani et al. [21] involves a deep neural network that forecasts the existence or absence of CKD. This study utilizes the CKD dataset from the UCI ML Repository. A large amount of data is needed to generalize well, which can be a limitation when dealing with small or imbalanced CKD datasets.

Al Imran et al. [22] stated that their primary focus in the research was to apply three modern ML techniques to diagnose CKD and determine the most effective technique by assessing their diagnostic performance. The real-time dataset is collected for the study. Upon assessment of these methods, the authors determined that the feedforward neural network exhibited the highest proficiency as a technique for diagnosing CKD.

Akter et al. [23] employed several clinical features of CKD and implemented seven advanced deep-learning algorithms for predicting and classifying CKD. The proposed algorithms utilized artificial intelligence techniques to extract and evaluate features. One limitation of the study is the small dataset size, potentially compromising the reliability of the results.

Amirgaliyev et al. [24] presented an automated classification algorithm for diagnosing kidney disease. It utilizes noninvasive and cost-effective factors like clinical history, physical exams, and lab tests. They assessed the SVM classifier with linear kernels to optimize sensitivity, specificity, and accuracy. However, the study lacks an in-depth exploration of potential drawbacks and contrasts with other medical methods in terms of screening and diagnosis.

Qin et al. [25] presented an ML approach to diagnose CKD. Real-time dataset was collected for the study, but it contained numerous missing values. To tackle this problem, KNN imputation was utilized, entailing the utilization of measurements from the nearest samples to fill in missing data for each incomplete sample. The model's ability to perform well on new data might be constrained, and it is unable to assess the severity of CKD since the dataset contains only two categories: "ckd" and "notckd." Rashed et al. [26] created machine learning models utilizing specific essential pathological categories to detect clinical test attributes that can facilitate precise and early diagnosis of CKD. The data with labelled samples was gathered from hospital-based resources.

Employing empirical analysis of diverse ML techniques, Khan et al. [27] categorized a dataset of kidney patients into two distinct groups: CKD and NOTCKD. 25 attributes describe each instance in the dataset. Seven different ML techniques were employed for classification. To assess the performance of these techniques, the authors used distinctive evaluation measures. Implementing and tuning seven different machine-learning approaches can be time-consuming and complex.

Chittora et al. [28], seven different classifier algorithms were employed. The authors used the CKD dataset from the UCI repository. The results indicate that the SMOTE technique proved to be the most effective method for balancing the dataset. Employing and optimizing seven distinct machine-learning approaches can be a time-consuming and intricate process. Furthermore, it was observed that SMOTE achieved superior outcomes when applied to the selected features. Jain et al. [29] introduced a rapid adaptive classification system designed for chronic disease diagnosis. The method utilizes a hybrid strategy that combines PCA and the Relief technique, along with an optimized SVM classifier.

Chronic Kidney Disease (CKD), associated with cardiovascular and renal risks, necessitates early detection. Yadav et al. [30] introduced a hybrid ML technique that combines a feature selection method with a classification algorithm. Relief-F and chi-squared methods identify crucial features, while six. The amalgamation of big data and ML shows promise in elevating healthcare value by accurately detecting CKD at its initial stages.

Vashisth et al. [31] aimed to enhance classification accuracy for chronic kidney disease diagnosis using a Neural Network classifier combined with four distinct feature techniques. The study explores feature reduction and relevance methods to optimize the neural network's performance. The experimental setup involves utilizing the neural network as an ensemble model with diverse feature techniques. The training phase employs 300 instances, constituting 75% of the chronic kidney disease dataset, while testing involves 100 cases. This approach seeks to improve disease classification accuracy, employing a combination of advanced techniques to identify the most relevant features and optimize the neural network's predictive capabilities.

3. Materials and Methods

The initial phase involves gathering the dataset, which is then subjected to preprocessing. Subsequently, the prepared data is utilized for the prediction process, where CNN is employed. The LSTM network used in this model analysed the temporal dependencies and patterns in sequential data. Upon constructing the corresponding model, notable enhancements in performance parameters are achieved. The diagram representing the proposed system can be observed in Figure 3.

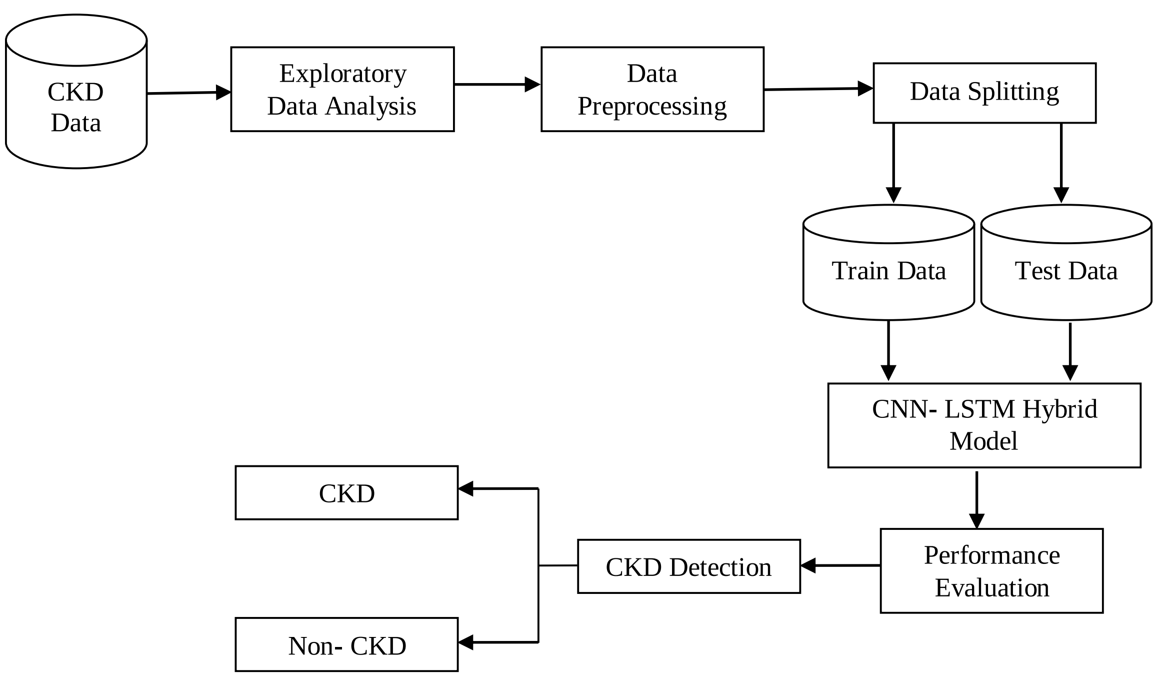

Fig. 3 Block diagram of proposed method

3.1. Dataset Description

The dataset of CSV files utilized for the detection of CKD was taken from the Kaggle repository. The dataset is a two-dimensional tabular data structure that can hold data in rows and columns. The dataset contains 400 samples with 37 different attributes for each sample. The dataset comprises essential clinical attributes, medical test results, and demographic information related to CKD patients to effectively capture spatial patterns and temporal dependencies within the data, respectively.

The dataset thus employed is passed through a hybrid method that combines CNN and LSTM architecture. It provides a substantial amount of information for the hybrid model to learn from and make more precise predictions, ultimately contributing to improved diagnostic outcomes for patients with CKD. By using the hybrid CNN-LSTM method on this dataset, we aimed to achieve enhanced accuracy and sensitivity in identifying CKD cases early on. The dataset is split into two subsets, dedicating 80% for training and 20% for testing objectives.

3.2. Data Preprocessing

The initial and critical phase in data analysis is the data preprocessing of CSV data, where raw data is prepared and refined to enhance its quality and suitability for further processing. The preprocessing typically involves loading the data, inspecting for missing values, and handling duplicates. The missing value of each column is verified to ensure the data's quality and to decide on appropriate strategies for handling missing data during data preprocessing. Count, mean, std, min, max, and three three-quartile values are the statistical parameters verified for each numerical column.

This information helps to quickly understand the distribution and range of the data in each numerical column. Visualization of data is shown in Figure 4. Correlation analysis is performed as it is helpful in feature selection. Features with high positive or negative correlations with the target variable can be considered more influential in predicting the target. They may be prioritized in machine learning models or data analysis-higher feature values in positive correlation are associated with a higher probability of CKD.

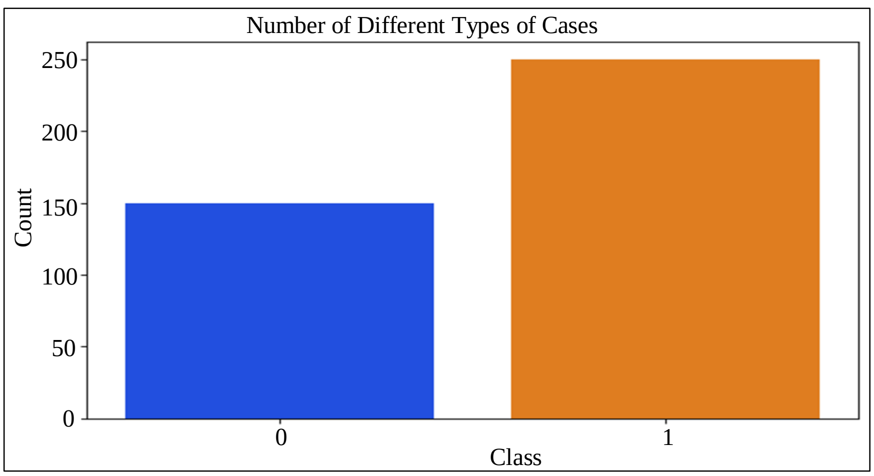

Fig. 4 Data visualization

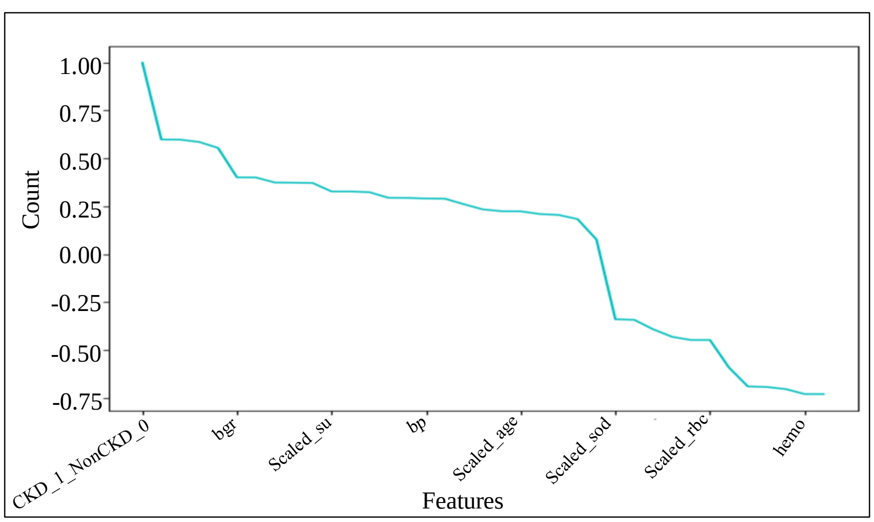

Fig. 5 Correlation of features with CKD

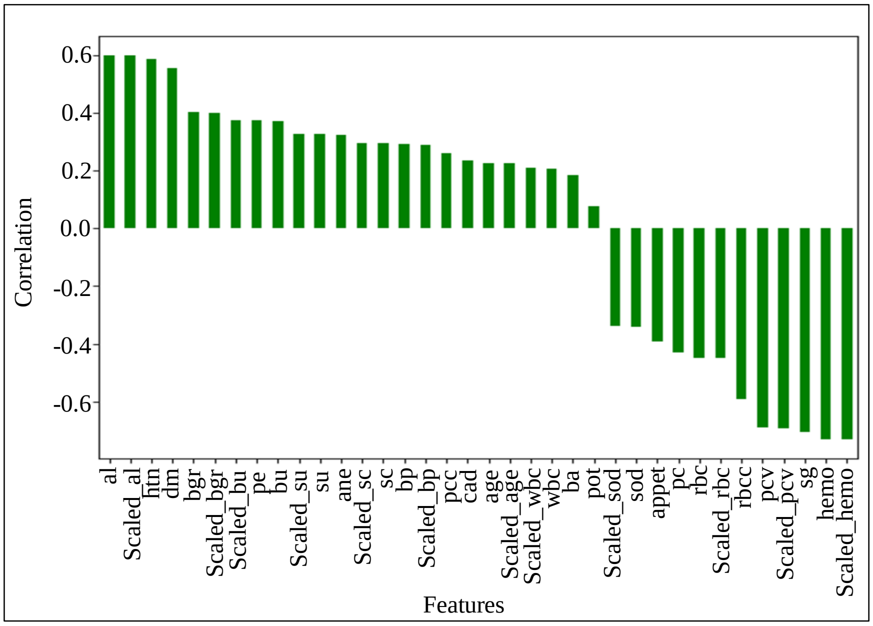

Fig. 6 Correlation with case type

Also, Higher feature values in negative correlation values are associated with a lower likelihood of CKD. A correlation value close to 0 indicates a weak or no linear relationship between the feature and the target variable. This means that changes in the feature value do not significantly affect the likelihood of having or not having CKD. The correlation of features with CKD is depicted in Figure 5.

The bar plot of the dataset is visualised in Figure 6, which shows the correlation of each feature with the target variable 'CKD_1_NonCKD_0'. The plot will display the association between each feature and the target variable. 'CKD_1_NonCKD_0' as vertical bars. The higher the bar, the stronger the correlation between the feature and the target variable.

3.3. Convolutional Neural Network (CNN)

CNN is a robust and widely used DL architecture specifically designed for processing and analyzing visual data. The architecture of a CNN is a DL model designed explicitly for visual data processing. It typically consists of input layers to receive raw data, convolutional layers for feature extraction using learnable filters, activation functions to introduce non-linearity, pooling layers for spatial dimension reduction, a fully connected layer for prediction, and an output layer for generating the final results.

CNNs leverage the hierarchical structure of these layers to learn and represent meaningful patterns in the data automatically. The basic CNN architecture is shown in Figure 7.

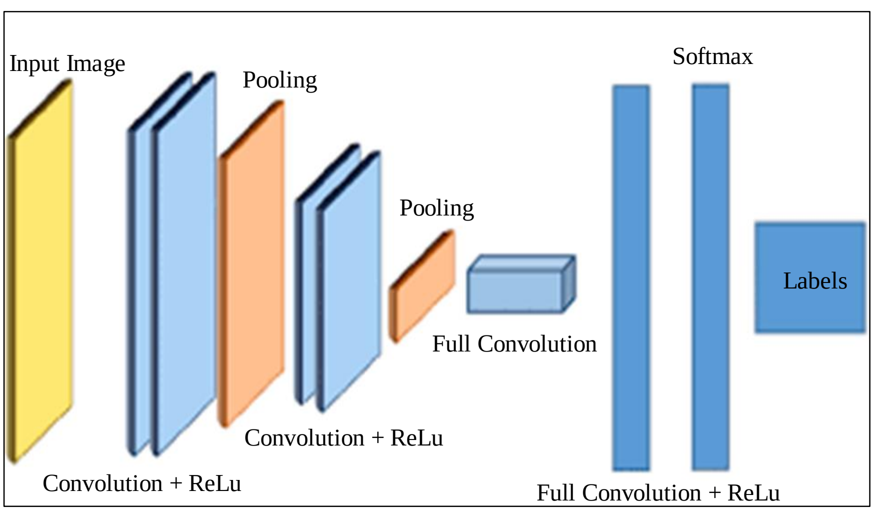

Fig. 7 Basic CNN architecture

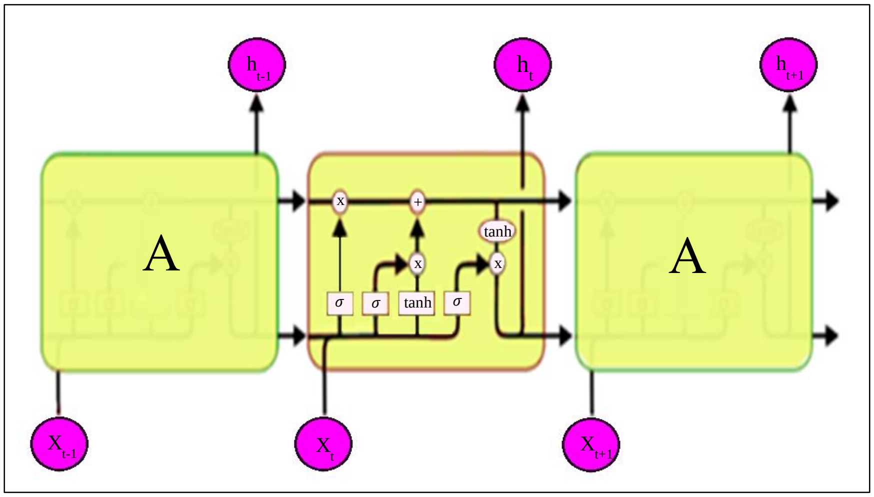

Fig. 8 Basic LSTM architecture

3.4. Long Short-Term Memory (LSTM)

The structure of an LSTM network constitutes a specific form of Recurrent Neural Network (RNN) crafted to comprehend and represent extended patterns in sequential data. The core components of an LSTM include input gates to control the flow of information into the memory cells, forget gates to regulate the retention of relevant information, and output gates to control the flow of information from the memory cells to the next time step.

This architecture addresses the vanishing gradient problem in traditional RNNs. It enables LSTM networks to effectively process and learn from sequential data, making them well-suited for tasks like natural language processing, time series analysis, and any other application where temporal dependencies are crucial for accurate predictions. Figure 8 shows the LSTM architecture.

3.5. Proposed Model Architecture

The suggested model comprises a trio of concealed layers with 100, 50, and 25 units, respectively, each using the ReLU activation function. The output layer has one unit with the sigmoid activation function, making it suitable for binary classification tasks. The structure of the proposed model's LSTM design includes two LSTM layers with 128 and 256 units, respectively.

The first layer processes the input sequence and returns the output for each time step, while the second layer processes the sequence and returns the output only for the last time step. To enhance model regularization, a dropout layer is introduced following the initial LSTM layer. The model's output is a solitary value using a sigmoid activation function, indicating the likelihood of a binary classification objective. The proposed model architecture is shown in Figure 9.

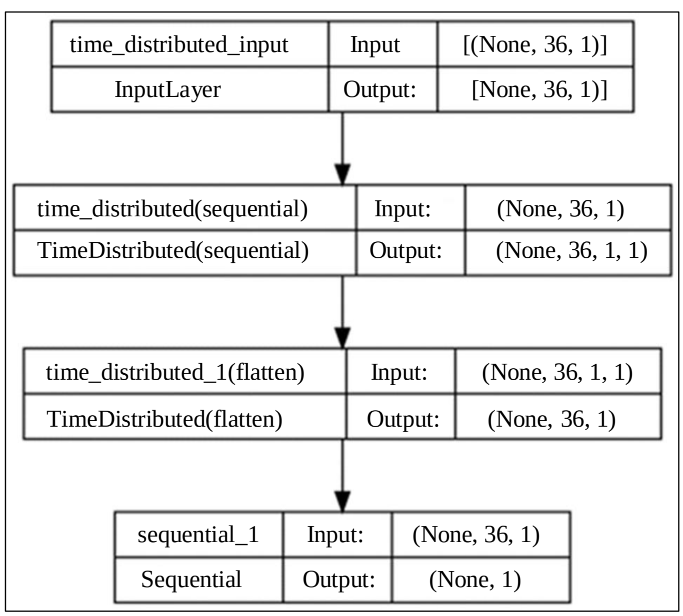

Fig. 9 Proposed model architecture

A Time Distributed LSTM model is added to the proposed model. It allows the LSTM model to process each time step of the input sequence independently. After the compilation process, the model is ready for training, where it will be trained on a given dataset, optimizing the specified loss function with the Adam optimizer and evaluated using the accuracy metric. A total of 467,608 parameters were used which all are trainable. The model uses 'Adam' as the optimization and 'Binary-Cross entropy' as the loss function.

3.6. Performance Parameters

In the context of evaluating the suggested model's performance, various performance indicators are available to gauge its effectiveness. The deep learning industry employs several standards to assess system performance, and in the following sections, we will explore some key metrics such as accuracy, Cohens kappa, precision, recall, specificity, F1-score. Table 1 provides the mathematical expression of various performance measures.

Table 1. Performance parameters

Parameters	Equation
Accuracy	$(TP + TN)/(TP + TN + FP + FN)$
Precision	$(TP)/(TP + FP)$
Recall	$(TP)/(TP + FN)$
F1- Score	$2 * \frac{(Precision \times Recall)}{(Precision + Recall)}$
TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative	

4. Results and Discussion

4.1. Hardware and Software Setup

To ensure a consistent and reliable computing environment, this research opts for Google Collaboratory and Microsoft Windows 10 as the preferred platforms. In this setup, the system boasts an Intel Core i7-6850K 3.60 GHz 12-core processor and one NVIDIA GeForce GTX 1080 Ti GPU 2760 4MB.

4.2. Experimental Results

After the dataset preparation, the proposed models were implemented using Python and TensorFlow. The training process of the model involved the application of the Adam optimization algorithm with a batch size of 40. During the training, we utilized accuracy and loss plots to gain valuable insights into the model's performance. The accuracy plot provided a visual representation of the correct prediction trend over training epochs, indicating the classification effectiveness. The loss plot depicted the gradual reduction in the model's error throughout training, showcasing its convergence towards an optimal solution. These plots served as valuable tools for detecting potential overfitting or underfitting issues and making well-informed decisions regarding necessary model adjustments or optimizations to enhance overall performance. The accuracy plot and loss plot of the model on the dataset are shown in Figure 10 and Figure 11, revealing an impressive accuracy of 98.75%. Table 2 provides the classification report of the proposed model.

The accuracy and loss plot of the proposed system is shown in Figure 10, Figure 11 provides a visual representation of its performance during the training process. It illustrates the increasing or stabilizing trend of the model's accuracy, which indicates its ability to classify data points correctly-the loss plot represents the discrepancy between the predicted output and the actual target values.

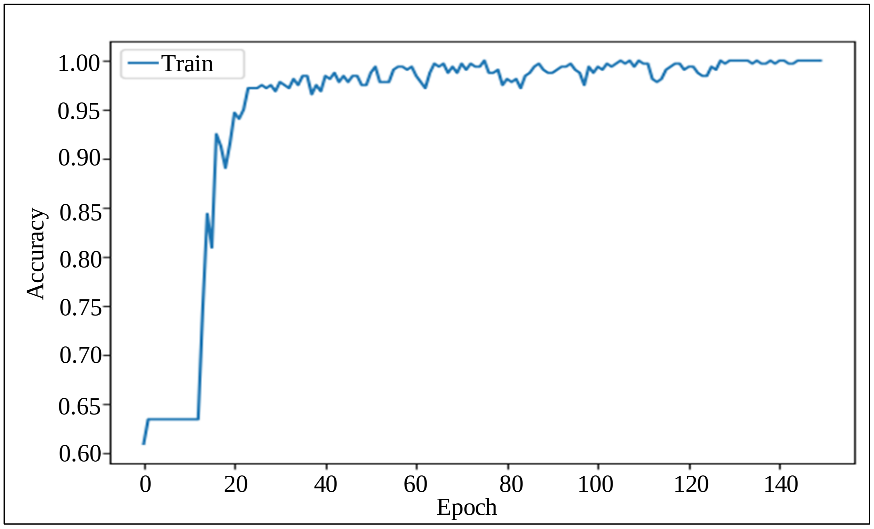

Fig. 10 Accuracy plot of the proposed system

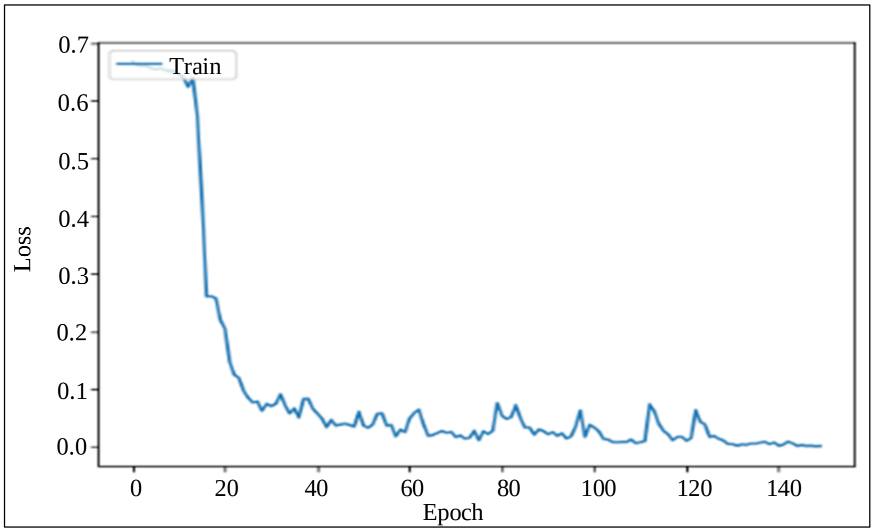

Fig. 11 Loss plot of the proposed system

Table 2. Classification report

Parameters	Value
Accuracy	98.75 %
Precision	100 %
Recall	97.87 %
F1- Score	98.92 %
Cohens Kappa	97.43 %
ROC AUC	98.93 %
Specificity	100 %

As the system iteratively learns from the data, the loss should ideally decrease, signifying that the model is minimizing its errors and becoming more accurate. The proposed system demonstrates outstanding performance, as reflected in the accuracy and loss plot. The accuracy plot shows a steady upward trend, indicating that the model consistently makes correct predictions as the training progresses. Additionally, the loss plot exhibits a substantial and consistent decrease, showcasing the system's ability to minimize errors and optimize its predictions effectively. These promising results signify the robustness and efficiency of our proposed system in tackling the given task with high precision and reliability.

The confusion matrix of the proposed model is shown in Figure 12 as a valuable tool for evaluating its performance in a classification task. The diagonal components of the confusion matrix denote accurate predictions (TP and TN), while the non-diagonal elements indicate inaccurate predictions (FP and FN). The ROC curve in Figure 13 illustrates the trade-off between the model's true positive rate (sensitivity) and the false positive rate (1-specificity) across different probability thresholds for classification. A value of 0.5 for the AUC-ROC indicates a classifier performing at random, whereas a value of 1.0 signifies an impeccable classifier.

Upon analyzing the table comparing our system with existing methods, it becomes evident that our system outperforms other approaches in several key aspects. It achieves higher accuracy rates, demonstrating its superior ability to make correct predictions for CKD. Additionally, our system exhibits improved precision and recall values, indicating its effectiveness in minimizing false positives and false negatives, respectively, leading to more reliable diagnoses. Furthermore, the F1 score of our system is significantly higher than that of the existing methods, signifying a better balance between precision and recall.

This balanced performance is crucial in accurately identifying high-risk individuals early and guiding appropriate personalized treatment plans. The Area Under the Receiver Operating Characteristic Curve (ROC AUC) score also shows a substantial improvement in our system, confirming its superior discriminative power in distinguishing between positive and negative CKD cases. Table 3 presents a performance comparison of the proposed method with existing methods.

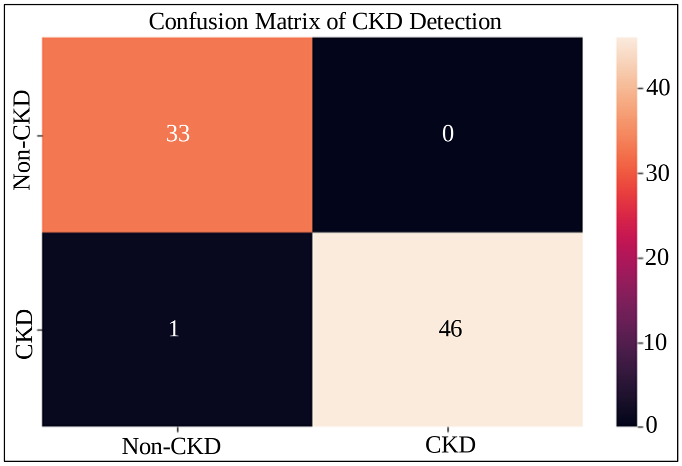

Fig. 12 Confusion matrix of the proposed system

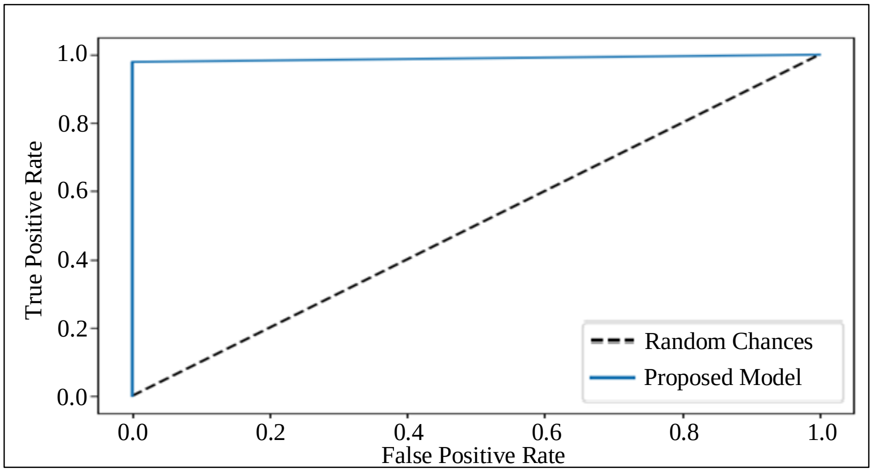

Fig. 13 ROC curve of the proposed system

Table 3. Contrasting the newly introduced system with established methodologies

Sl. No.	Author, Year & Reference	Methodology	Accuracy (%)	Precision (%)	Recall (%)	F1- Score (%)	Specificity (%)
1	Amirgaliy ev et al. [24], 2018	Support Vector Machine	93	-	93.10	-	94.20
2	Jain et al. [29], 2021	PCA and Relief Method with Optimized SVM Classifier	97.48	100	71.43	83.33	-
3	Vashisth et al. [32], 2020	Multi-layer Perception Classifier	92.5	-	-	93	1
4	Ravindra et al. [33], 2018	Feedforward Backpropagation Neural Network	95.3	-	100	-	90
5	Kriplai [21], 2019	CNN	97	100	95.2	97.6	-
6	Suresh et al. [34], 2020	Artificial Neural Network	96	-	-	-	-
7	Bhaskar et al. [35], 2019	CNN, SVM	96.59	97.2	94.59	95.8	98.03
8	**Proposed Method**	**CNN- LSTM**	**98.75**	**100**	**97.87**	**98.9**	**100**

5. Conclusion

CKD is a serious and widespread health concern, affecting millions of people worldwide. Early detection of CKD is crucial in preventing disease progression, as it allows for timely intervention, resulting in tailored treatment approaches, ultimately culminating in enhanced patient results. This study successfully demonstrates the potential of utilizing a CNN model with LSTM units for the prompt identification of CKD through the utilization of CSV data.

The dataset collected from the Kaggle repository was efficiently used for the prediction process. The CNN-LSTM model showcased impressive performance, achieving an accuracy rate of 98.75%. This remarkable accuracy indicates the model's ability to identify CKD effectively. Cases, thereby highlighting the value of deep learning-based diagnostic tools in the field of medical research. The high accuracy rate suggests that the CNN-LSTM model can serve as a reliable and efficient tool for aiding clinicians in the early identification and management of CKD. The success of this study further encourages further research and development in the field of artificial intelligence and its potential to revolutionize healthcare practices.

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