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Exploring Deep Learning Approaches for Early Detection of CKD: Trends and Techniques

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This study investigates the application of deep learning models, namely CNN, RNNs, and MLP, for the early prediction of CKD. Early detection of CKD is critical for initiating timely treatment, as the disease can advance with few symptoms. The research leverages a preprocessed Kaggle dataset, divided for training and testing, to assess model performance. Among the models, CNN achieved an impressive 99% accuracy, highlighting its strong feature extraction capabilities. The RNN and MLP models also demonstrated high accuracy, reinforcing the potential of deep learning in enhancing CKD screening processes. This approach can support more personalized and preventive healthcare, potentially improving patient outcomes through earlier interventions.
Keywords: RNN, CKD, Deep Learning, CNN, ANN, LSTM, Performance Optimization

Abbreviation	Full Form
CKD	Chronic Kidney Disease
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
MLP	Multi-Layer Perceptron
ANN	Artificial Neural Network
LSTM	Long Short-Term Memory (a type of RNN)

Introduction:

Chronic Kidney Disease (CKD) is a significant global public health issue, with prevalence on the rise due to aging populations and increasing rates of diabetes, hypertension, and lifestyle changes [1]. If untreated, CKD progressively worsens, ultimately leading to End-Stage Renal Disease (ESRD), where kidney function is severely compromised, often necessitating dialysis or kidney transplantation to sustain life [2]. Affecting approximately 10% of the global population, CKD's impact is expected to grow as risk factors like obesity and diabetes become more common [3]. The disease also leads to reduced quality of life, with high morbidity and mortality rates, as well as significant healthcare costs [4]. Thus, early and accurate diagnosis of CKD is crucial to enable timely treatment and prevent progression to advanced stages.

Early detection of CKD allows for prompt interventions, which can positively influence patient outcomes and slow disease progression. Preventive measures, including lifestyle changes, blood pressure control, and medication, can be implemented early, potentially reducing the need for more costly treatments later on [5]. However, CKD's silent progression, often without early symptoms, makes early detection challenging. Traditional CKD diagnostics rely on laboratory markers, such as serum creatinine and blood urea nitrogen levels, along with clinical evaluations of symptoms and risk factors [6]. While effective, these methods can be invasive, time-consuming, and costly, and may not always detect CKD in its earliest stages [7].

Advances in technology have enabled the development of predictive models that analyze patient data to identify individuals at risk of CKD before symptoms appear [8]. Such models offer the potential for proactive interventions and personalized treatment, which can improve patient quality of life while also reducing long-term healthcare costs [9]. Deep learning has revolutionized medical diagnostics, enabling more sophisticated data analysis. Models such as CNN, RNNs, and MLP have demonstrated exceptional performance in various medical applications by automating the feature extraction process and leveraging patient data [10].

CNNs, in particular, excel with structured data and images, making them valuable for tasks such as analyzing X-rays and MRIs, where they detect local patterns and spatial relationships through convolution layers [11]. This capacity to recognize subtle patterns makes CNNs well-suited for diagnosing complex diseases like CKD [12]. RNNs, especially (LSTM) networks, are specialized for sequential data, making them beneficial for analyzing time-series data in patient monitoring due to their ability to capture temporal dependencies [13][14]. Meanwhile, simpler architectures like MLPs, with densely connected layers, can effectively classify data given proper feature engineering, making them useful for structured data like patient records [15].

The use of deep learning models for CKD prediction can significantly enhance diagnostic performance without requiring manual feature extraction. These models can manage large datasets and reveal hidden associations that may not be apparent with standard statistical analysis, thus fostering new strategies for early detection and patient stratification [16]. Healthcare stands to benefit substantially from the ongoing integration of deep learning methods, which promise to drive improvements in patient outcomes over time.

Traditional CKD diagnostic methods, including laboratory tests and clinical evaluations, are not only invasive and costly but also limited in detecting early-stage CKD[17]. This study underscores the need for more sensitive, non-invasive, and accurate predictive tools. By applying deep learning models—such as CNNs, RNNs, and MLPs—this research aims to improve CKD prediction by uncovering subtle patterns in complex medical data that might otherwise go undetected[18]. The goal is to advance early CKD detection, allowing for timely intervention and potentially extending or saving patient lives.

The main contributions of this research include:

- Evaluating the performance of CNN, RNN, and MLP models for CKD prediction to determine the most accurate model.
- Identifying key features influencing CKD prediction to improve model interpretability and diagnostic insights.
- Developing an integrated forecasting model combining CNNs, RNNs, and MLPs to enhance prediction accuracy for CKD.

The remainder of this paper is organized as follows: Section 2 reviews previous research on CKD prediction and the application of deep learning in medical diagnostics. Section 3 describes the dataset, including feature selection, preprocessing, and the rationale behind the chosen models. This section also provides an overview of the methodology, detailing the architectures and implementation of CNN, RNN, and MLP models for CKD prediction. Section 4 presents experimental results, comparing the models and evaluating their effectiveness using various metrics. Section 5 discusses the results and explores their implications for clinical practice and future research. The conclusion summarizes the study's key findings, contributions, and recommendations for advancing CKD prediction.

Related Work:

This study conducts an in-depth review of machine learning applications for predicting CKD, focusing on how these methods enhance diagnostic precision, treatment, and preventive strategies[19]. The review evaluates a range of algorithms, including decision trees, support vector machines (SVMs), ensemble methods, and deep learning techniques, to highlight current gaps and challenges in CKD prediction. The goal is to explore the potential for machine learning to provide more accurate, objective, and less invasive early detection methods[20][21][22].

CKD is a significant global health issue due to its progressive nature and its impact on quality of life[23]. Traditional diagnostic methods, such as lab tests and clinical assessments, often require invasive procedures, presenting a need for more efficient predictive tools that can improve early detection without compromising patient comfort become a valuable tool in CKD prediction by leveraging large datasets to identify complex patterns within patient data[24]. Machine learning as decision trees, SVMs, and ensemble techniques have shown promise in CKD prediction. Decision trees offer a straightforward approach by categorizing patients based on clinical characteristics, though they may struggle with wiensional data. SVMs, known for accurately distinguishing between classes, have demonstrated good results in CKD classification, though they are computationally demanding and sensitive to hyperparameter settings[25][26]. Ensemble models, like Random Forest Machines, combine multiple models to increase predictive accuracy and mitigate overfitting, particularly in data with complex feature interactions.

CKD affects over 10% of the world's population and progages, with early detection being critical for successful management. Although serum creatinine and blood urea nitrogen (BUN) are commonly used inail to detect early-stage CKD[27]. New diagnostic tools are essential to facilitate early intervention, improve patient outcomes, and reduce healthcare costs [28]. Deep learning techniques, which automatically perform feature extraction on complex data, offer solutions for CKD prediction by minimizing the need for manual data preprocessing. CCNN, which excels in analyzing medical images, has shown effectiveness in kidney scans, making them useful for CKD detection. RNNs, especially (LSTM) networks, capture temporal dependencies, making things sequential patient data over time [29].

This study leverages the strengths of CNNs, RNNs, and MLP to predict CKD. RNNs capture temporal patterns within patient CNNs process medical imaging data, and MLPs interpret non-linear relationships in structured clinical data. By integrating these models, we aim to enhance prediction accuracy and overcome previous limitations in feature extraction and model adaptability[30].

Our review shows significant advancements in machine learning models for CKD diagnosis, though gaps remain in combining different deep learning approaches to maximize predictive power[31][32]. This study addresses these gaps by integrating RNNs, CNNs, and MLPs, combining each model's unique advantages to improve early CKD detection, accuracy, and reliability across diverse clinical environments. This unified model not only boosts diagnostic capability but also sets a foundation for new approaches in CKD management and patient care[33].

Material and Methods:

This section details the dataset, proposed architecture, preprocessing steps, and the three deep learning techniques implemented to predict CKD and evaluate model performance. This study leverages deep-learning models specifically designed for kidney disease prediction.

Proposed Architecture:

The proposed architecture for CKD prediction integrates multiple deep learning models, each chosen to optimize predictive accuracy by targeting specific characteristics of the clinical dataset. This architecture combines CCNN, RNNs and MLP, with each model applied based on its strengths in handling different data types.

CNNs, typically used for image data, are adapted here for tabular data to capture complex hierarchical features and non-linear relationships within CKD parameters. The CNN structure includes one-dimensional convolutional layers, which detect local dependencies between features, combined with pooling layers to improve computational efficiency. LSTM networks, as part of the RNN model, are applied to capture temporal dependencies, modeling changes in patient health over time—an essential factor in CKD prediction. MLPs focus on structured clinical data, identifying intricate relationships (e.g., between blood pressure and serum creatinine levels).

This architecture employs a unified framework in which outputs from the CNN, RNN, and MLP models are combined using a soft voting scheme, providing a weighted average for the final prediction. By integrating these models, the proposed approach maximizes the strengths of each technique, improving both accuracy and reliability in CKD prediction. Figure 1 provides an overview of the model's design, illustrating the flow of information and the decision-making process within the proposed model.

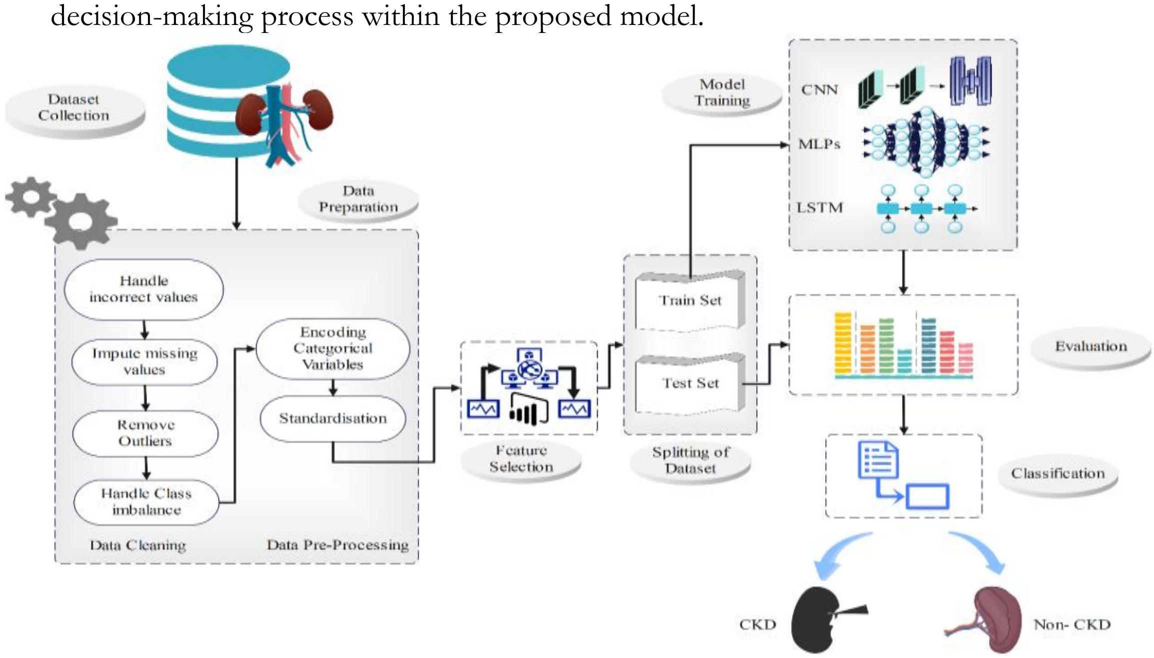

Figure 1. Proposed Architecture

CKD Dataset:

This study utilizes a CKD dataset available on Kaggle, a reputable platform for diverse and high-quality datasets. The CKD dataset includes essential clinical and demographic information relevant to CKD diagnosis and management, such as blood pressure, serum creatinine, blood urea, hemoglobin levels, and indicators for conditions like diabetes and hypertension. Feature selection is based on each parameter's clinical significance in assessing kidney function and its relevance to CKD risk stratification.

Table 1 provides a detailed description of the dataset, covering numerical features like age, blood pressure (BP), and serum creatinine (SC), as well as categorical variables such as the presence of diabetes mellitus (DM) and coronary artery disease (CAD).

Table 1. Dataset Parameters

Parameter	Description	Parameter	Description
id	Unique identifier assigned to each patient record	sod	Serum Sodium; abnormal levels may be influenced by kidney function
age	Patient's age, critical for understanding CKD prevalence and progression	pot	Serum Potassium; levels may be affected by kidney function
bp	Systolic blood pressure, a key measure related to kidney disease risk	hemo	Hemoglobin levels; anemia is common in CKD patients
sg	Specific Gravity of urine; abnormal values may suggest kidney dysfunction	pcv	Packed Cell Volume; low levels may indicate anemia related to kidney disease
al	Albumin in urine; elevated values can indicate kidney damage	wc	White Blood Cell count; high counts may suggest inflammation or infection affecting kidney function
su	Sugar in urine; high levels may signal diabetes, a common cause of kidney disease	rc	Red Blood Cell count; indicates blood health and kidney function
rbc	Red Blood Cells in urine; abnormal levels may indicate kidney damage or other conditions	htn	Hypertension, a common risk factor for kidney disease, recorded as binary (yes/no)
pc	Pus Cells in urine; presence may indicate inflammation or infection affecting kidney function	dm	Diabetes Mellitus, another risk factor, recorded as binary (yes/no)
pcc	Pus Cell Clumps in urine; may indicate severe infection or inflammation	cad	Coronary Artery Disease, a condition linked to CKD risk, recorded as binary (yes/no)
ba	Bacteria in urine; may suggest a urinary tract infection affecting kidney function	appet	Appetite level, which can be affected by kidney disease, categorized as good or poor
bgr	Blood Glucose Random; high levels may indicate	pe	Pedal Edema presence; fluid retention can be a

	diabetes, a significant risk factor for kidney disease		symptom of CKD
bu	Blood Urea; elevated levels may indicate impaired kidney function	ane	Anemia, common in CKD patients, recorded as binary (yes/no)
sc	Serum Creatinine; high levels often correlate with reduced kidney function	Classification	Target variable indicating CKD presence, categorized as 'ckd' (with CKD) or 'notckd' (without CKD)

This dataset provides a thorough collection of features for CKD modeling, encompassing both clinical measurements and patient demographics. The inclusion of such a wide array of parameters allows for a comprehensive analysis of the factors contributing to CKD and supports the development of predictive models for better diagnosis and management.

Data Preprocessing (Label Encoder):

Data preprocessing is a critical step in preparing the dataset for machine learning models, particularly when working with clinical data such as CKD. This process involves cleaning, transforming, and structuring the raw data to ensure that it is suitable for training models, which can ultimately improve the accuracy of predictions.

Handling Missing Data:

Imputation:

The dataset may contain missing values, which can lead to biased or inaccurate model outcomes. For numerical features, such as age, blood pressure, or serum creatinine, missing values are imputed using the mean of the existing data for that feature. For categorical variables (e.g., diabetes mellitus or hypertension), the mode (most frequent category) is used for imputation. This ensures that the dataset remains complete and usable for training the models.

Removal of Incomplete Records:

In instances where a large proportion of a record is missing, or the missing values cannot be reliably imputed, such records are removed from the dataset to maintain data integrity.

Normalization of Numerical Features:

Scaling:

Features in the dataset (such as age, serum creatinine, and blood pressure) can vary significantly in magnitude. To prevent any one feature from disproportionately affecting model performance, normalization is applied. This step scales each numerical feature to a range between 0 and 1, ensuring that all features contribute equally to the model's learning process.

Benefits:

Normalization speeds up model training by enabling faster convergence and improving the accuracy of predictions. It ensures that features with larger scales do not overshadow those with smaller scales.

Label Encoding of Categorical Variables:

Label Encoding:

Since machine learning models require numerical input, label encoding is used to convert categorical variables into numerical format. Binary variables such as hypertension (htn), diabetes mellitus (dm), and the target classification (CKD or non-CKD) are encoded as 1 (Yes) or 0 (No). For example, the presence of hypertension (htn) might be encoded as 1 (present) and 0 (absent).

Impact on Model Training:

Label encoding transforms categorical data into a format that can be efficiently processed by machine learning models, thus allowing the model to recognize and learn patterns associated with each category. Through these preprocessing steps, the data is transformed into a clean, normalized, and encoded format, ready for input into machine learning models. This approach ensures that the models can make predictions with greater accuracy and generalize better to unseen data.

Splitting the Dataset into Training and Testing:

To properly evaluate the performance of the deep learning models and ensure they generalize well to new, unseen data, it is essential to split the dataset into training and testing subsets. This process prevents overfitting and ensures that the models are not simply memorizing the training data but instead learning patterns that can be applied to new cases.

Training and Testing Split:

Training Set:

Typically, 80% of the data is used for training the models. This portion is used to teach the CNN, RNN, and MLP models to recognize patterns within the data, such as relationships between clinical features (e.g., blood pressure, serum creatinine) and the likelihood of CKD.

Testing Set:

The remaining 20% of the data is held out for testing purposes. This data is used to evaluate the model's performance on new, unseen examples. The testing set serves as an unbiased estimate of the model's predictive ability.

Preventing Overfitting:

By ensuring that the model is trained on one subset of the data and tested on another, we can assess whether the model is overfitting. Overfitting occurs when a model performs exceptionally well on training data but fails to generalize to new data. Testing on a separate dataset allows us to detect overfitting and adjust the model to improve its generalization capabilities.

Consistent Evaluation:

To ensure fairness in evaluating different models, the same data split is used for each model (CNN, RNN, and MLP). This consistent testing methodology allows for a direct comparison of the performance of each model on the same testing data, providing insights into which model performs best for predicting CKD. The careful splitting of the dataset into training and testing subsets is essential for assessing the model's ability to generalize to real-world clinical applications. It provides a realistic estimate of how the models will perform when deployed in practice.

Model Training Using CNN, RNN, And MLP:

In this research, three different deep learning models—**C**CNN, RNNs, and MLP—are used to predict CKD from clinical datasets. These models each bring unique strengths in learning from clinical features and medical data.

CCNN:

Application to Tabular Data:

Although CNNs are traditionally used for image processing, they can also be adapted to work with tabular data, such as clinical records. The CNN model in this study learns hierarchical features from the input data and captures complex patterns associated with CKD progression. By using one-dimensional convolution layers, the model automatically detects dependencies between clinical features, such as the relationship between blood pressure and serum creatinine levels.

Advantages: CNNs can effectively identify local patterns and non-linear relationships in the dataset, making them well-suited for capturing intricate dependencies in CKD-related clinical parameters.

RNNs :

Modeling Temporal Dependencies:

RNNs, specifically (LSTM) networks, are used to model temporal dependencies within the data. Since CKD progression depends on a patient's medical history and changes over time, LSTMs are well-suited for this task. These networks excel in learning from sequential data, where the order of events is important.

Benefits:

LSTMs can retain information over long sequences, making them effective in predicting CKD based on a patient's medical history. The model can capture patterns such as how past health conditions (e.g., hypertension, diabetes) influence CKD progression.

Multi-Layer Perceptrons :

Learning Non-Linear Relationships:

MLPs are a class of feedforward neural networks that consist of multiple layers of neurons. They are used to learn non-linear relationships between input features. In the context of CKD, MLPs process structured clinical data (e.g., age, serum creatinine, and blood pressure) and identify interactions between variables.

Strength:

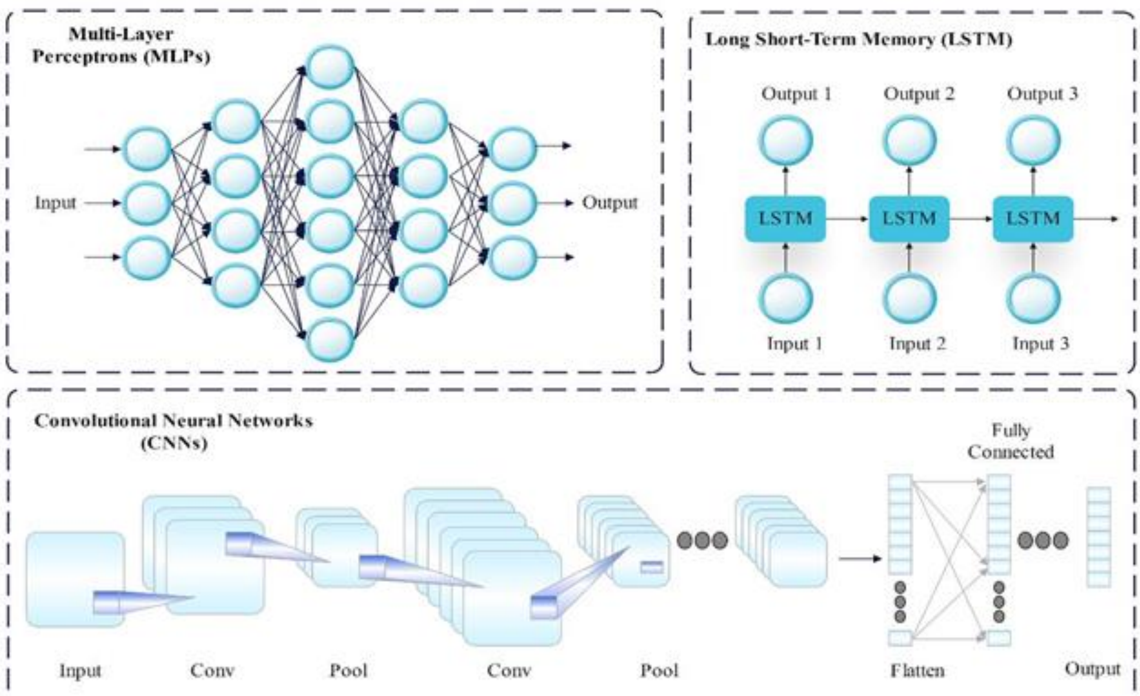

Figure 2. Neural Network Models

MLPs are highly effective in learning complex, non-linear associations, which is crucial when dealing with medical datasets that involve numerous factors influencing CKD risk. Each model is trained separately using the training dataset, where they learn from the patterns present in the clinical features. Once trained, the models are evaluated using the testing dataset to determine their predictive power in diagnosing CKD.

Choosing the Best Model for Prediction and Model Testing:

Based on the performance metrics, it is clear that the selected model exhibits high accuracy and excels in other key evaluation metrics, including precision, recall, and F1 score. These metrics collectively indicate that the model is highly effective for predicting CKD. In particular, the balance between sensitivity and specificity is optimal, suggesting that the model is well-suited for real-world clinical applications where both false positives and false negatives need to be minimized. After selecting the best-performing model, further refinements are made through hyperparameter tuning and additional testing on the training dataset. This fine-tuning process enhances the model's performance, ensuring that it has strong calibration and can effectively adapt to real-world variations in the data. This step is crucial for improving the robustness of the model, making it less sensitive to minor changes or shifts in data when deployed in clinical environments. Once these optimizations are complete, the model undergoes a rigorous testing phase using a completely separate, blind dataset. This external validation ensures that the model performs well on new, unseen data, providing an assessment of its ability to generalize beyond the training and validation datasets. The testing phase is vital for confirming the model's predictive power in practical, real-world scenarios, where it will often be applied to patient populations that were not included in the training data.

The results from this phase validate the model's ability to achieve a high level of predictive accuracy while minimizing both false positives and false negatives. Successful testing confirms that the model is ready for deployment in clinical settings, where it can be trusted to deliver reliable and accurate results at scale. Given the potential impact on healthcare applications, particularly in improving CKD diagnosis and treatment management, the model's ability to generalize effectively across different patient groups is essential for ensuring better healthcare outcomes and more informed decision-making.

RESULTS AND DISCUSSION:

The experiments for our proposed CKD prediction model were executed on Google Colab, a powerful and accessible environment for training and evaluating machine learning models. Using the resources available on Colab, we developed and tested deep learning models, including CCNN, RNNs, and MLP. In this section, we present the performance of these models and compare them to other approaches in predicting CKD.

Loading the Necessary Libraries:

The first step in the analysis and model development involved importing the necessary libraries. We utilized pandas and numpy for data processing, while matplotlib.pyplot and seaborn were used for visualizing the data. The train_test_split, StandardScaler, and LabelEncoder functions from sklearn were employed to split the dataset, scale the features, and encode categorical variables, respectively. The classification_report and confusion_matrix from sklearn allowed for evaluating the classification model's performance. Additionally, the models were saved using joblib. For building and training the deep learning models, we used tensorflow.keras with functions such as Sequential**,** Dense, Conv1D, MaxPooling1D, Flatten, LSTM, and Dropout. The to_categorical function was used to convert the class labels into a format suitable for classification.

Loading the CKD Dataset:

The next step involves loading the CKD dataset, which is stored as a CSV file named 'data.csv' in the content directory. We used the pd.read**csv** function to load the dataset into a pandas DataFrame. This initial step sets up the data for further cleaning and analysis.

Visualization of the CKD Dataset:

After loading the dataset, we proceeded to explore and visualize the distribution of the data. Using Seaborn'scountplot function, we plotted the number of CKD and non-CKD instances in the dataset. This graph, labeled "Count of CKD and Non-CKD," provides insights into the class distribution within the dataset. The distribution is shown in Figure 3, helping us understand the balance (or imbalance) between the two classes, which is crucial for model evaluation and further analysis. The visualization process aids in identifying potential issues such as class imbalance that might need to be addressed before model training.

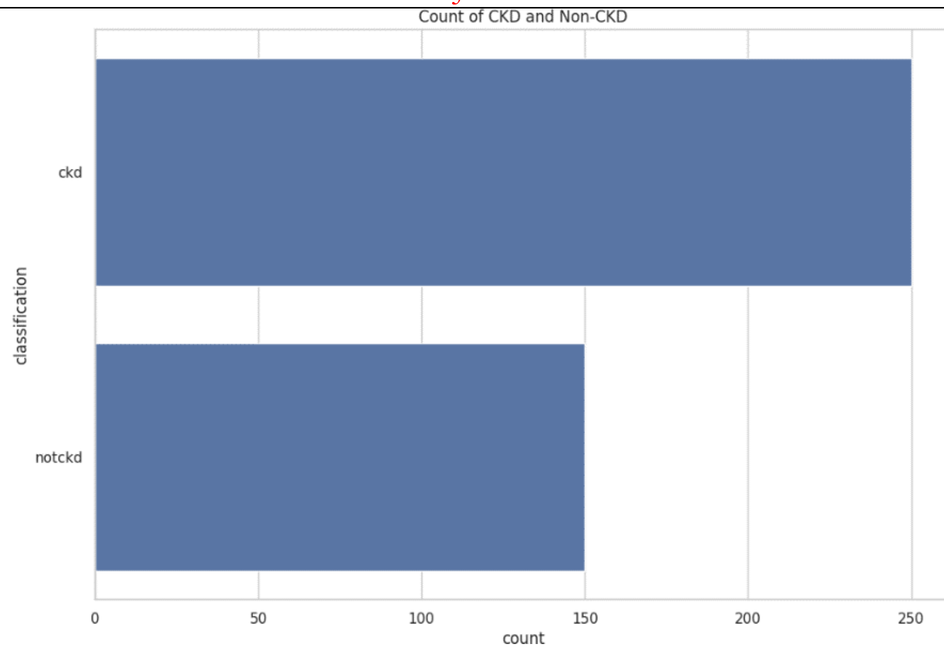

Figure 3. Count of CKD and Non-CKD

To better understand the age distribution in the dataset, we used Seaborn's histplotwith the kde=True parameter, which overlays a smooth Kernel Density Estimate (KDE) curve onto the histogram. This combination offers a clearer view of the age distribution among the patients and highlights the probability density. The plot is titled 'Age Distribution' and is displayed using Pl. Show (). This visualization is valuable for identifying the specific age range of the patients and understanding how the ages are spread across the dataset, as shown in Figure 4.

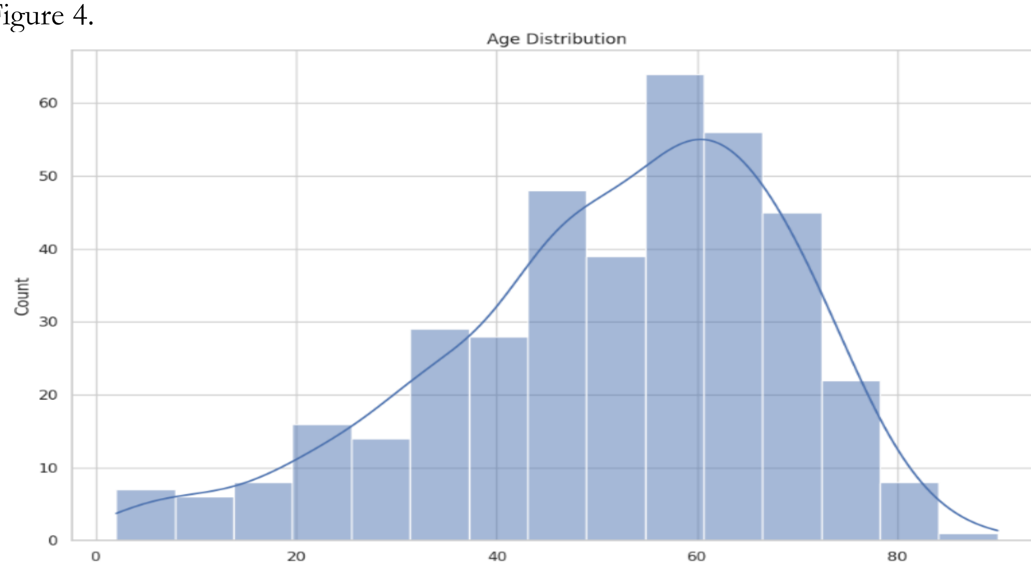

Figure 4. Age Distribution

This snippet includes a few additional libraries that are necessary for the analysis and uses a LabelEncoder to convert the categorical columns in the dataset to numeric values. Afterward, the modified dataset is outputted, and the correlation matrix is calculated to explore the relationships between the features. Finally, Figure 5 displays the correlation matrix as a heatmap, which visually represents the strength and direction of the relationships between the features.

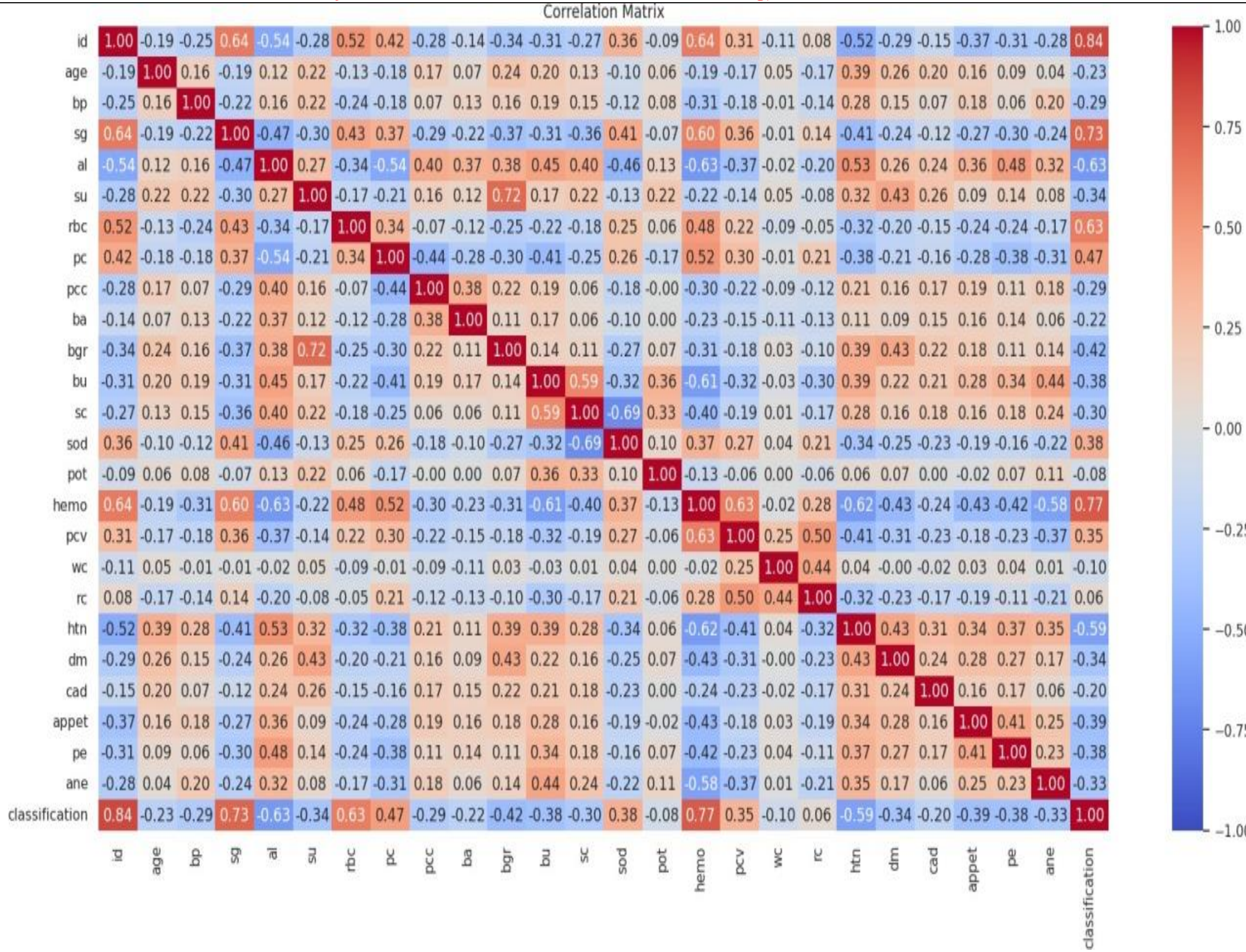

Figure 5. Correlation Matrix

Dataset Preparation and Preprocessing for Model Training:

To prepare the dataset for model training and testing, we first separate the dataset into feature variables (X) and the target variable (Y). Any missing values are identified and handled, with numerical columns being imputed using the mean and categorical columns filled using the mode. After handling missing data, categorical variables are encoded numerically. Next, the StandardScaler is applied to scale the features, and the target variable is also encoded for consistency. Finally, the dataset is split into training and testing sets in an 80% to 20% ratio for model evaluation.

Model Training for CKD Prediction:

The dataset undergoes necessary transformations to make it suitable for training with different deep learning models, including CCNN and RNNs. For CNN training, an additional axis is added to the testing dataset to accommodate the 1D convolutional layers. The CNN model architecture consists of sequential layers, including convolutional layers, max pooling, flattening, and dense layers. The model is compiled using the Adam optimizer and binary cross-entropy as the loss function, and it is trained for 5 epochs with 20% of the data reserved for validation.

For the RNN model, the data is transformed appropriately to work with LSTM layers. The RNN model is composed of one LSTM layer and two dense layers, and it is compiled using the Adam optimizer and binary cross-entropy loss. The model is trained for 5 epochs, with 20% of the data used for validation. For the Multi-Layer Perceptron (MLP) model, no additional reformatting of the data is needed, as the dataset remains in its initial form. The MLP model consists of dense layers with drop-out regularization, and it is compiled with the Adam optimizer and binary cross-entropy loss function. The training is conducted for 5 epochs, with 20% reserved for validation.

Model Evaluation and Classification Reports:

After training the three models (CNN, RNN, and MLP), they are evaluated using the test dataset. Predictions are made for each model, where values greater than 0.5 are considered as belonging to the positive class. Performance metrics, such as accuracy**,** precision**,** recall, and F1-score, are calculated and detailed in the classification reports. These results provide insights into how well each model performs in predicting CKD, and the classification reports (Tables 2, 3, and 4) offer a comparison of the performance of the CNN, RNN, and MLP models in terms of their ability to accurately predict CKD.

Table 2: Classification Report of CNN

Class	Precision	Recall	F1-Score	Support
0 (Non-CKD)	0.98	1.00	0.99	52
1	1.00	0.96	0.98	28
Accuracy			0.99	80
Macro Avg	0.99	0.98	0.99	80
Weighted Avg	0.99	0.99	0.99	80

Table 3: Classification Report of RNN

Class	Precision	Recall	F1-Score	Support
0 (Non-CKD)	0.91	0.77	0.83	52
1	0.67	0.86	0.75	28
Accuracy			0.80	80
Macro Avg	0.79	0.81	0.79	80
Weighted Avg	0.82	0.80	0.80	80

Table 4: Classification Report of MLP

Class	Precision	Recall	F1-Score	Support
0 (Non-CKD)	0.98	1.00	1.00	52
1	1.00	0.99	0.96	28
Accuracy			0.99	80
Macro Avg	1.00	1.00	1.00	80
Weighted Avg	1.00	1.00	1.00	80

These tables clearly display the classification metrics (Precision, Recall, F1-Score, and Support) for each class (Non-CKD and CKD) for the CNN, RNN, and MLP models, as well as the overall accuracy, macro average, and weighted average for the models.

Accuracies Comparison of Models:

In this section, we evaluate the performance of three deep learning models—CNN, RNN, and MLP—using accuracy as the primary evaluation metric. The models are tested using the test dataset, and their respective accuracies are obtained through the evaluation process. For this comparison, reshaped test data is used for both the CNN and RNN models, while the original test data is utilized for the MLP model.

The accuracies for each model are stored in a dictionary, where the model names—CNN, RNN, and MLP—serve as the keys, and their corresponding accuracy values are the values. This dictionary is then used to generate a bar chart with the help of the matplotliblibrary. The chart displays the model names on the x-axis and their accuracy values on the y-axis, providing a clear visual representation of how each model performs in predicting CKD.

The bar chart, shown in Figure 6**,** offers a comparative analysis of the three models, highlighting which one achieves the highest accuracy in CKD prediction. This comparison will be used to determine the best-performing model for future CKD detection tasks.

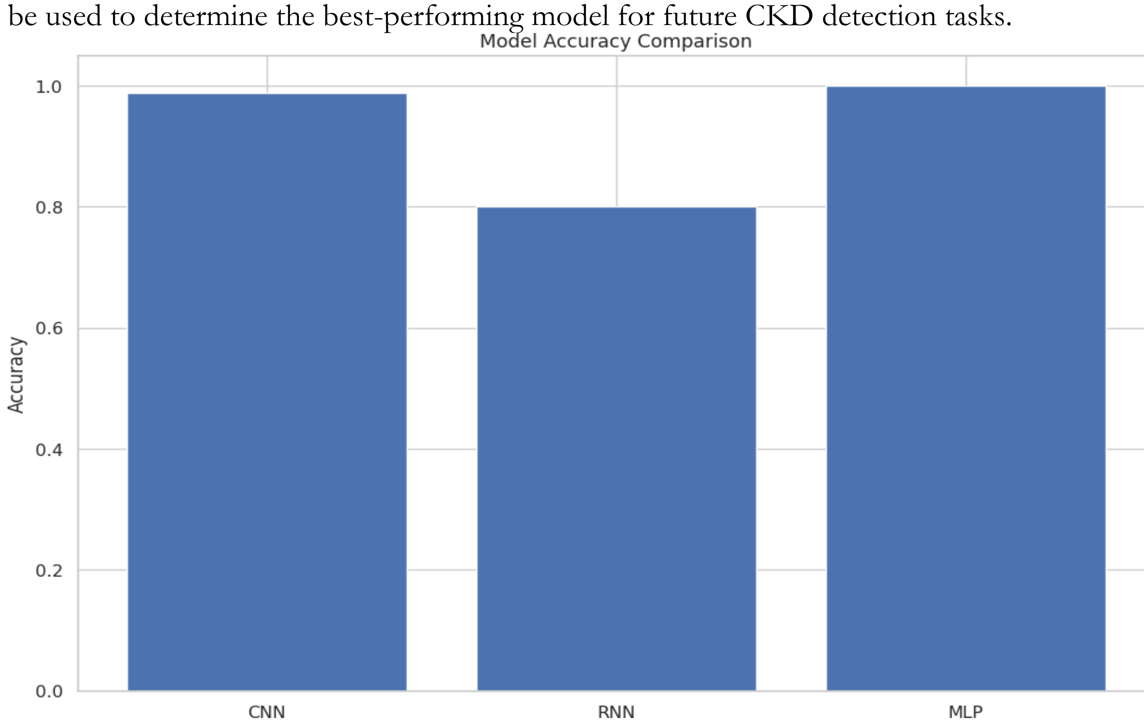

Figure6. Accuracy ComparisonofModels

Conclusion:

This study focused on predicting CKD using deep learning algorithms, specifically CNN, RNN, and MLP, which were trained on clinical data. Through data preprocessing, model training, and performance evaluation, we demonstrated the advantages of each model. The CNN model excelled at capturing hierarchical features, the RNN model effectively handled temporal relationships, and the MLP model showed strong performance with structured data.

These models were implemented in a practical setting using Flask. Our findings indicate that combining these models provides a deeper understanding of CKD prediction, contributing to better patient care. We observed differences in performance across the models: the CNN model achieved the highest accuracy and predictive ability for CKD detection, while the RNN model was more efficient at capturing sequential dependencies. The MLP model proved effective with structured clinical data.

Key preprocessing techniques, such as normalization and encoding of categorical variables and handling missing values, were critical in improving model performance and ensuring their generalization to new data. Additionally, deploying the models through Flask allowed real-time testing, confirming their clinical applicability.

The study highlighted that integrating different deep learning models can lead to improved CKD prediction, with potential applications in early diagnosis and patient management in clinical practice. For future work, we plan to expand our training and testing datasets to further enhance model accuracy by reducing patient condition variability. We also aim to incorporate techniques such as ensemble learning and transfer learning to further improve prediction performance. Ultimately, the goal is to enhance the accuracy and timeliness of CKD detection, enabling earlier intervention and better patient outcomes.

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