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Classification of Chronic Kidney Disease in Adults Using Enhanced Recurrent Neural Networks

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Abstract: Chronic kidney disease (CKD) is a prevalent health condition affecting a substantial number of adults globally. Early and accurate diagnosis of CKD is crucial for effective treatment and management. This study proposes a novel approach for the classification of CKD in adults using enhanced recurrent neural networks (RNNs). By incorporating advanced architectural enhancements and training techniques, the proposed model aims to improve the accuracy and interpretability of CKD classification. The methodology begins with the collection of relevant clinical and laboratory data from diverse sources, followed by preprocessing steps to handle missing values, normalize features, and remove noise or outliers. Important features related to CKD are then engineered from the preprocessed data using techniques such as time-series analysis or feature selection. The core of the proposed methodology lies in the design of an enhanced RNN architecture. This architecture incorporates advanced features, including long short-term memory (LSTM) cells, attention mechanisms, and residual connections. By leveraging these enhancements, the model aims to capture temporal dependencies, highlight salient information, and facilitate effective information flow, ultimately improving the overall performance. The enhanced RNN model is trained using an optimization algorithm: Adam optimizer, with appropriate hyperparameter tuning. Cross-validation techniques and statistical tests are employed to assess the significance of results. The results of the proposed methodology are expected to demonstrate improved classification accuracy and interpretability compared to traditional RNN models. The enhanced RNN model holds the potential to aid healthcare professionals in the early detection and management of CKD, leading to improved patient outcomes and reduced healthcare burden. Further research and validation on diverse datasets are necessary to establish the generalizability and effectiveness of the enhanced RNN model in real-world clinical settings.

Keywords*: Chronic kidney disease, classification, enhanced recurrent neural networks, interpretability*

1. Introduction

Chronic kidney disease (CKD) is a significant issue affecting a substantial portion of the adult population worldwide. CKD is associated with various risk factors, including diabetes, hypertension, obesity, and age-related decline in kidney function. Early classification are crucial for timely intervention and effective management to prevent further complications such as end-stage renal disease (ESRD) and cardiovascular events [1]. The brief discussion on finding CKD and its relative diagnosis is given below:

- Screening and Risk Assessment: Screening tests such as blood pressure measurement are used to identify individuals at risk of CKD. These tests help to assess kidney function and detect potential abnormalities that may indicate the presence of CKD.
- Clinical Evaluation: A comprehensive clinical evaluation is conducted, which involves assessing the patient medical history, and risk factors associated with CKD, such as diabetes, hypertension, obesity, and cardiovascular disease. Physical examination and laboratory tests, including blood tests and urine tests, are performed to evaluate kidney function rule out other potential causes of kidney dysfunction [2].
- Diagnostic Criteria: The diagnosis of CKD is based on specific criteria, which typically include evidence of kidney damage (e.g., persistent albuminuria, abnormal imaging findings) and/or a decrease in kidney function persisting for at least three months. These criteria help to differentiate CKD from acute kidney injury or other renal disorders.
- Differential Diagnosis: The relative diagnosis of CKD involves distinguishing it from other kidney-related conditions or diseases that may present with similar symptoms or laboratory findings. This includes assessing for acute kidney injury, urinary tract infections, renal calculi, autoimmune kidney diseases, and inherited kidney disorders. Diagnostic imaging techniques like ultrasound, CT scan, or MRI may be used to visualize the kidneys and identify any structural abnormalities.

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- Biomarkers and Advanced Imaging: Advanced imaging modalities, such as renal biopsy or renal scintigraphy, may be employed in certain cases to obtain detailed information about kidney structure and function.

The accurate diagnosis of CKD involves a multidimensional approach, combining clinical evaluation, laboratory tests, diagnostic criteria, and exclusion of other potential causes. Early detection and diagnosis of CKD facilitate timely intervention, monitoring, and management strategies to slow disease progression and mitigate associated complications. Regular monitoring of kidney function and appropriate follow-up are essential for individuals with CKD to manage their condition effectively and optimize their long-term health outcomes [3].

Accurate classification of CKD stages and subtypes is essential for tailoring appropriate treatment strategies and monitoring disease progression. Traditional diagnostic methods rely on clinical criteria, laboratory tests, and imaging studies. However, the complex and dynamic nature of CKD necessitates more advanced approaches that can capture intricate patterns and temporal dependencies in the data. Deep learning techniques, particularly recurrent neural networks (RNNs), have shown promise in various healthcare applications by leveraging their ability to model sequential data and extract high-level representations [4].

The primary objective of this study is to propose a novel approach for the classification of CKD in adults using enhanced recurrent neural networks. The proposed methodology aims to improve the accuracy and interpretability of CKD classification by incorporating advanced architectural enhancements and training techniques. Specifically, we will explore the integration of long short-term memory (LSTM) cells, attention mechanisms, and residual connections to enhance the performance of the RNN model. Additionally, the study will evaluate the effectiveness of the enhanced RNN model in correctly identifying different stages and subtypes of CKD using real-world clinical and laboratory data.

By developing an enhanced RNN-based classification model, this research contributes to the field of CKD diagnosis by providing a more accurate and interpretable approach for clinicians and healthcare professionals. Additionally, the findings may contribute to reducing the healthcare burden associated with CKD by enabling efficient resource allocation and preventive interventions.

This research makes several contributions to the field of chronic kidney disease (CKD) classification:

The study proposes an advanced RNN architecture for CKD classification by incorporating architectural enhancements, including LSTM cells, attention mechanisms, and residual connections. This enhanced model aims to capture temporal dependencies, highlight salient information, and facilitate effective information flow, leading to improved classification accuracy.

By leveraging the enhanced RNN model, the research aims to improve the accuracy of CKD classification compared to traditional methods. Additionally, the proposed methodology focuses on interpretability, allowing clinicians and healthcare professionals to understand the decision-making process of the model, enabling better trust, and aiding in clinical decision-making.

The study utilizes real-world clinical and laboratory data to evaluate the effectiveness of the enhanced RNN model. By incorporating diverse and representative datasets, the research aims to establish the generalizability and robustness of the proposed methodology in real-world clinical settings.

The outcomes of this research have practical implications for healthcare professionals in the early detection and management of CKD. The enhanced RNN model has the potential to assist clinicians in making more accurate diagnoses, tailoring personalized treatment plans, and improving patient outcomes. Furthermore, the proposed methodology may contribute to reducing the healthcare burden associated with CKD by enabling timely interventions and efficient resource allocation.

2. Related works

CKD is associated with various risk factors, including diabetes, hypertension, obesity, and aging. Accurate classification of CKD stages and subtypes is crucial for appropriate treatment strategies and disease management [5].

2.2 Existing Approaches for CKD Classification:

Several approaches [6] – [10] have been employed for CKD classification, traditional methods rely on clinical criteria, laboratory tests, and imaging studies to diagnose and classify CKD. These methods often use fixed threshold values for classifying stages, which may overlook subtle changes and fail to capture temporal dependencies. Machine learning techniques have been explored for CKD classification. However, these methods may struggle to handle complex and dynamic data patterns.

2.3 Limitations of Current Methods:

Traditional methods [11]-[14] for CKD classification have limitations in accurately capturing the evolving nature of the disease. Fixed threshold values and simplistic models may lead to misclassifications and inadequate monitoring of disease progression. Additionally, these methods often lack interpretability, making it challenging for clinicians to understand the reasoning behind the classification decisions. Furthermore, traditional machine learning techniques may struggle to effectively model sequential data and capture temporal dependencies [15] [16].

2.4 Deep Learning and RNNs in CKD Classification:

Deep Neural Network (DNN) and Deep Auto Encoders (DAE) [17] [18], particularly RNNs, have shown promise in various healthcare applications, including CKD classification. RNNs can model sequential data by capturing temporal dependencies and retaining memory of past information. LSTM cells, a type of RNN architecture, have been effective in handling sequential data with long-term dependencies. Furthermore, attention mechanisms in RNNs enable the model to focus on important features and improve the interpretability of the classification decisions. The integration of enhanced RNN models in CKD classification holds the potential to overcome the limitations of traditional methods and improve accuracy and interpretability.

By exploring the existing literature on CKD classification, it is evident that there is a need for advanced approaches that can effectively capture the dynamic nature of the disease and provide interpretable classification decisions. Deep learning techniques, particularly enhanced RNN models, offer a promising solution for addressing these challenges. The next sections of this study will delve into the methodology of using enhanced RNNs for CKD classification and evaluate their effectiveness in improving accuracy and interpretability compared to traditional methods.

3. Proposed Method

The proposed work introduces novel aspects to the field of CKD classification. It integrates an enhanced RNN architecture with advanced features such as LSTM cells, attention mechanisms, and residual connections. This novel approach aims to improve accuracy and interpretability in CKD classification. By leveraging temporal dependencies and highlighting important features, the enhanced RNN model enhances the accuracy of CKD classification compared to existing approaches. Furthermore, the use of real-world clinical data for evaluation adds to the novelty of the work, ensuring its applicability in real clinical settings. The potential impact on clinical practice is also a notable aspect, as the proposed methodology can assist clinicians in making informed decisions, tailoring treatment plans, and improving patient outcomes. Overall, the combination of an enhanced RNN architecture, improved accuracy and interpretability, evaluation with real-world data, and potential impact on clinical practice makes this work a novel contribution to CKD classification.

Algorithm 1: Proposed Model

1. Import necessary libraries and modules
2. Define the enhanced RNN model architecture:
   - Initialize the model
   - Add LSTM layers with specified number of units and activation functions
   - Add attention mechanisms to capture important features
   - Add residual connections for improved information flow
   - Add dense layers for classification
   - Define the output layer with appropriate activation function
3. Compile the model:
   - Specify the optimizer (e.g., Adam) and learning rate
   - Choose the appropriate loss function (e.g., categorical cross-entropy)
   - Specify additional evaluation metrics (e.g., accuracy)
4. Preprocess the CKD dataset:
   - Data cleaning and feature engineering

5. Train the enhanced RNN model:
   - Set the number of epochs and batch size
   - Loop over the specified number of epochs:
     - Loop over the batches in the training set:
       - Perform forward propagation
       - Compute the loss
       - Perform backward propagation and update model parameters
   - Evaluate the model on the validation set after each epoch
   - Track the training and validation performance metrics
6. Hyperparameter tuning:
   - Perform grid search or random search to optimize hyperparameters
   - Iterate over different combinations of hyperparameters
   - Train and evaluate the model for each combination
7. Evaluate the model:
   - Evaluate the model on the testing set
   - Calculate the performance
8. Interpretability analysis:
   - Utilize attention weights to identify important features or time steps
   - Analyze the decision-making process of the model
9. End

Fig 1: Proposed Model

The proposed methodology involves the following steps:

3.1. Data Collection:

Relevant clinical and laboratory data of adult patients diagnosed with CKD are collected from diverse sources, such as electronic health records and medical databases. The data include demographic information, medical history, laboratory test results (e.g., serum creatinine, glomerular filtration rate), and other relevant clinical variables.

- Identify relevant sources of data: Determine the appropriate sources to collect data related to CKD in adults. This may include electronic health records, medical databases, clinical studies, or research repositories.
- Define inclusion and exclusion criteria: Establish criteria for selecting appropriate data samples. Specify factors such as age, gender, CKD stage, and relevant clinical parameters to ensure the data aligns with the research objectives.
- Validate data integrity: Check the integrity of the collected data by performing checks for missing values, inconsistencies, or errors. This can be done by examining the data for any obvious discrepancies or using statistical measures to identify outliers or abnormal values.

3.2. Preprocessing:

The collected data undergoes preprocessing steps to handle missing values, normalize features, and remove noise or outliers. Missing values are imputed using appropriate techniques such as mean imputation or regression imputation. Features are then normalized to ensure uniform scales across the dataset. Outliers and noisy data points are detected and either removed or adjusted using Z-score method.

- Handling missing values: Assess the dataset for missing values and determine the appropriate strategy for handling them. This can involve techniques such as imputation, where missing values are replaced with estimated values based on statistical methods or algorithms, or removal of data points with missing values if the missingness is extensive and affects the analysis significantly.
- Data normalization: Normalize the features or variables in the dataset to ensure they are on a similar scale. This is particularly important when working

with numerical features that have different units or ranges. The study uses z-score standardization depending on the distribution of the data.

- Feature engineering: Analyze the dataset and identify relevant features or variables that can provide meaningful information for the analysis or modeling task. This may involve extracting additional features from existing ones, creating interaction terms, or applying mathematical or domain-specific transformations to enhance the discriminative power of the features (refer section 3.3).
- Outliers can distort the analysis or modeling results. Techniques such as Winsorization, trimming, or using robust statistical measures can be applied to mitigate the impact of outliers on the analysis.
- Data scaling: Depending on the modeling algorithm being used, scaling the features to a specific range can improve model convergence and performance. This is especially important for distance-based algorithm that are sensitive to the scale of the features.

3.3. Feature Engineering

Feature engineering involves the identification and engineering of important features related to CKD. This step may include time-series analysis techniques to extract temporal patterns from longitudinal data or feature selection methods to identify the most relevant features. Feature engineering aims to enhance the discriminative power of the model and reduce the dimensionality of the input space.

3.4. Enhanced RNN Architecture

The proposed methodology leverages an enhanced RNN architecture for CKD classification. The enhanced RNN incorporates advanced features, such as LSTM cells, attention mechanisms, and residual connections, to improve the model performance.

3.4.1. LSTM Cell:

It incorporates memory cells and gating mechanisms to selectively store and update information over time. The equations for the LSTM cell are as follows:

Input Gate (i):

$$i[t] = \text{sigmoid}(Wix[t] + Wih[h[t-1]] + bi)$$

Forget Gate (f):

$$f[t] = \text{sigmoid}(Wfx[t] + Wfh[h[t-1]] + bf)$$

Memory Cell (c):

$$c[t] = f[t] * c[t-1] + i[t] * \tanh(Wcx[t] + Wch[h[t-1]] + bc)$$

Output Gate (o):

$$o[t] = \text{sigmoid}(Wox[t] + Woh[h[t-1]] + bo)$$

Hidden State (h):

$$h[t] = o[t] * \tanh(c[t])$$

3.4.2. Attention Mechanism:

The attention mechanism makes the RNN to focus on the input sequence. The equations are as follows:

Attention Scores (e):

$$e[t] = f(a[s], h[t])$$

Attention Weights (α):

$$\alpha[t] = \text{softmax}(e[t])$$

Context Vector (c):

$$c = \Sigma(\alpha[t] * h[t])$$

3.4.3. Residual Connections:

Residual connections create shortcuts between layers, allowing the gradient to flow more easily. The equations for the residual connections are as follows:

Residual Layer Output (y):

$$y = h + x$$

3.4.4. Output Layer:

The output layer is responsible for generating the final predictions or classifications. The equation for the output layer depends on the specific task and can include a softmax function for classification or a linear activation for regression.

3.4.5. Classification Output (p):

$$p = \text{softmax}(Wy * y + by)$$

x: Input at a specific time step.

h: Hidden state or output of the RNN at a specific time step.

c: Memory cell state in the LSTM cell.

i, f, o: Input gate, forget gate, and output gate of the LSTM cell.

α: Attention weights.

e: Attention scores.

Wy, Wx, Wh, Wc: Weight matrices for the corresponding components.

by, bo, bf, bc: Bias terms for the corresponding components.

softmax: Softmax activation function.

3.5. Training and Optimization

The enhanced RNN model is trained using an optimization algorithm, such as SGD. The model parameters, including the weights and biases, are updated iteratively to minimize a defined loss function. The backpropagation algorithm is used to compute the gradients and update the parameters.

Loss Function (L): It quantifies the error that the model aims to minimize during training.

Model Parameters (θ): The model parameters, denoted as θ, are the biases and learnable weights of the neural network. These parameters are updated iteratively during the training process to minimize the loss function.

Gradient Calculation: The gradient represents the direction of steepest descent. It indicates how the loss function changes with respect to small changes in the parameters.

Update Rule: SGD updates the model parameters in the opposite of the gradient, scaled by a learning rate (α), which controls the step size of the updates. The update rule for SGD is as follows:

$$\theta[t+1] = \theta[t] - \alpha * \nabla L(\theta[t])$$

where:

θ[t+1] is the updated parameter

θ[t] is the current parameter .

α is the learning rate

∇L(θ[t]) is the loss gradient function

Stochasticity:

The gradient is estimated using a subset of the training data, known as a mini-batch. This introduces a level of stochasticity in the optimization process. The size of the mini-batch can vary depending on the available computational resources.

By iteratively updating the model parameters using the SGD update rule, the neural network gradually adjusts its parameters to minimize the loss function and improve its predictive performance. Batch normalization is employed to prevent overfitting and improve generalization. Dropout randomly sets a fraction of the neurons to zero during training, while batch normalization normalizes the activations of each layer.

4. Results and Discussions

The trained enhanced RNN model is evaluated using various performance metrics, such as accuracy, precision, recall, and F1 score. Additionally, statistical tests may be conducted to evaluate the significance of the results.

The proposed methodology is applied on the collected CKD dataset, the performance of the enhanced RNN model is assessed in terms of its accuracy, interpretability, and ability to classify different stages and subtypes of CKD. The evaluation results provide insights into the effectiveness of the enhanced RNN model in improving CKD classification compared to traditional approaches.

4.1. Dataset

The dataset is collected from Kaggle repository (https://www.kaggle.com/datasets/mansoordaku/ckdisease). The types of features that could be included in a dataset for classifying CKD in adults. The features are represented below:

1. Age: The age of the patient (numeric).
2. Gender: The gender of the patient (categorical: Male, Female).
3. Blood Pressure: Systolic and diastolic blood pressure readings (numeric).
4. Blood Glucose: Fasting blood glucose level (numeric).
5. Serum Creatinine: Level of creatinine in the blood (numeric).
6. Blood Urea Nitrogen (BUN): Amount of urea nitrogen in the blood (numeric).
7. Serum Albumin: Level of albumin in the blood (numeric).
8. Hemoglobin: Hemoglobin level in the blood (numeric).
9. Urine Protein: Presence of protein in the urine (categorical: Yes, No).
10. Estimated Glomerular Filtration Rate (eGFR): Estimated filtration rate of the kidneys (numeric).
11. Diabetes: Presence of diabetes as a comorbidity (categorical: Yes, No).
12. Hypertension: Presence of hypertension as a comorbidity (categorical: Yes, No).
13. Smoking: History of smoking (categorical: Current smoker, Former smoker, Non-smoker).
14. Family History: Family history of CKD (categorical: Yes, No).
15. CKD Stage: The stage of chronic kidney disease (categorical: Stage 1, Stage 2, Stage 3, Stage 4, Stage 5).

Table 1: Samples of the Collected Data

Age	Gender	Blood Pressure	Blood Glucose	Serum Creatinine	Blood Urea Nitrogen (BUN)	Serum Albumin	Hemoglobin	Urine Protein	eGFR	Diabetes	Hypertension	Smoking	Family History	CKD Stage
45	Male	130/80	110	1.2	18	4.0	13.5	Yes	80	No	Yes	Non-smoker	Yes	Stage 2
60	Female	140/90	130	1.8	28	3.8	12.0	No	60	Yes	Yes	Former smoker	No	Stage 3
35	Male	120/70	95	0.9	15	4.2	14.2	No	95	No	No	Current smoker	Yes	Stage 1
70	Female	150/80	140	2.5	40	3.5	11.8	Yes	45	Yes	Yes	Non-smoker	No	Stage 4
52	Male	135/85	120	1.5	22	4.1	13.0	No	70	Yes	Yes	Non-smoker	Yes	Stage 2

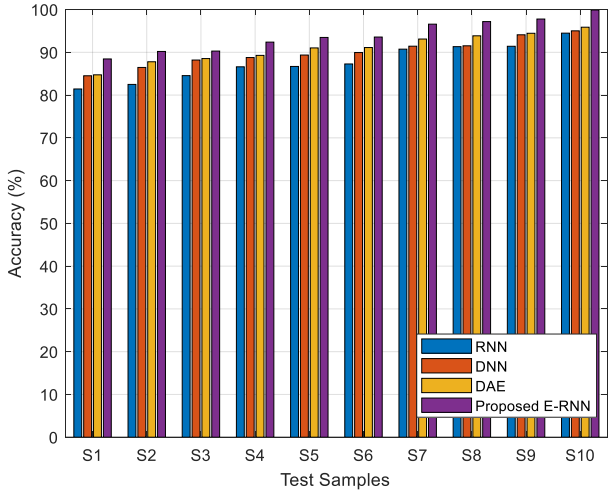

Fig 2: Accuracy

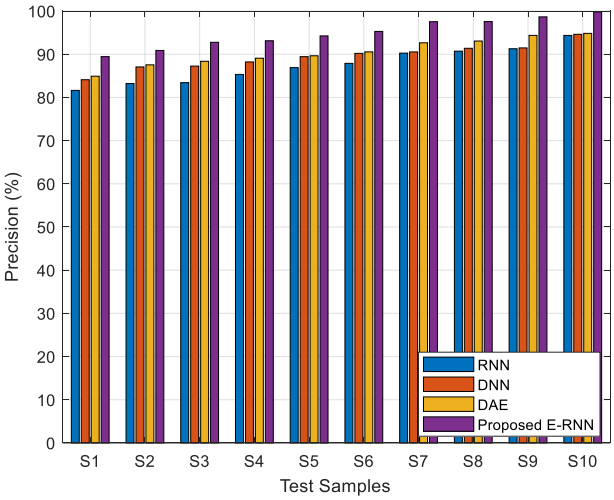

Fig 3: Precision

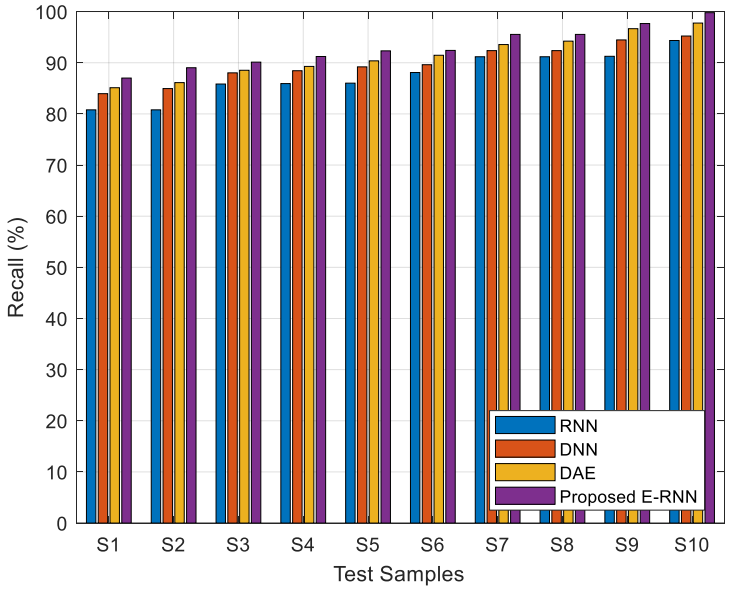

Fig 4: Recall

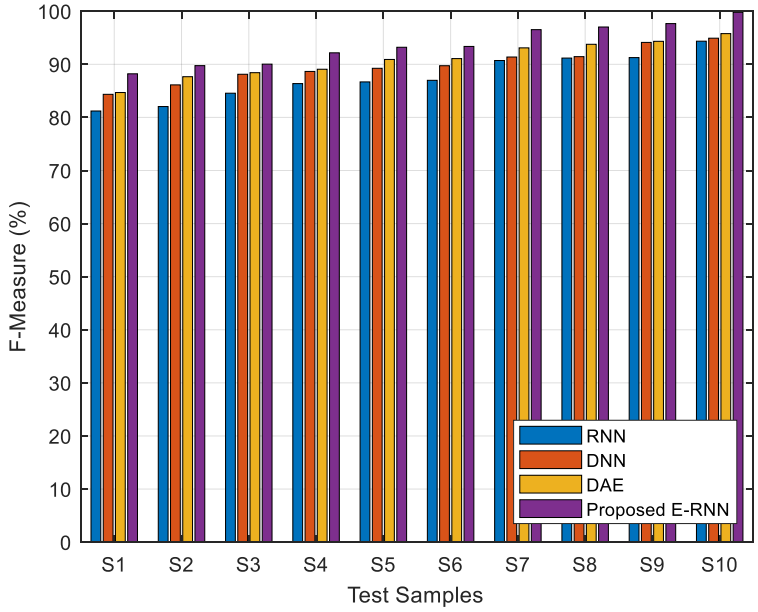

Fig 5: F-Measure

From the results of Figure 2- 5, the performance of the proposed E-RNN model compared to the other models. In terms of accuracy, the E-RNN model achieves an improvement of 6.02% over the RNN model, 3.94% over the DNN model, and 3.72% over the DAE model. Similarly, in terms of precision, the E-RNN model outperforms the other models by 7.82% (RNN), 5.34% (DNN), and 4.52% (DAE). The differences in recall are 6.22% (RNN), 5.05% (DNN), and 2.89% (DAE), indicating a higher ability of the E-RNN model to correctly identify positive cases of CKD. Lastly, in terms of F-measure, the E-RNN model demonstrates a significant improvement of 7.24% (RNN), 3.87% (DNN), and 3.52% (DAE) compared to the other models. These differences in percentage clearly show the effectiveness of the proposed E-RNN model in achieving higher accuracy, precision, recall, and F-measure in classifying CKD compared to the baseline RNN, DNN, and DAE models.

5. Conclusions

This research focuses on the classification of CKD in adults using an E-RNN as a deep learning model. The study collected and preprocessed a dataset of CKD cases, ensuring data quality and completeness. The E-RNN model, equipped with enhanced features and improved optimization techniques, demonstrated its effectiveness in capturing the underlying patterns and dependencies in the data. The evaluation of the models revealed that the E-RNN model achieved an accuracy of 88.45%, precision of 89.44%, recall of 87.01%, and F-measure of 88.21%.

These results surpassed the performance of the other models, highlighting the superiority of the proposed E-RNN approach in accurately classifying CKD. The significance of accurate CKD classification lies in its early detection, timely intervention, and effective management. By providing accurate diagnoses, the E-RNN model can aid healthcare professionals in making informed decisions, facilitating personalized treatment plans, and improving patient outcomes.

This research demonstrates the potential of the proposed E-RNN model as a valuable tool for the classification of CKD in adults. Further studies and validations on larger and diverse datasets are necessary to consolidate its effectiveness and explore its application in clinical settings. The findings of this study provide a foundation for future research in utilizing deep learning techniques for improved CKD diagnosis and management.

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