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RESEARCH ARTICLE

Chronic Kidney Failure Risk Prediction and Phase-Wise Progress Classification Via Simple Recurrent Neural Network (SRNN) Approach

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Abstract

Objectives: To create a robust classification framework to identify and classify the different stages of CKD as per standard medical guidelines based on patient data. To develop an accurate predictive model for assessing the risk of progression from Chronic Kidney Disease (CKD) to Kidney Failure using a Simple Recurrent Neural Network (SRNN). To enhance early detection of CKD progression by enabling timely medical intervention and by improving patient outcomes. **Methods:** To obtain the right accuracy of results, a Simple Recurrent Neural Network (SRNN) method is used for both prediction and classification purposes. The methodology leverages a multi-phase classification system that is trained with clinical datasets. In this work, a dataset named "Chronic Kidney Disease" from the UCI Machine Learning Repository is used. This dataset is modified by adding two attributes called 'eGFR' and 'stage-class'. **Findings:** The key features like estimated Glomerular Filtration Rate (eGFR), blood pressure, and creatinine levels are utilized to classify CKD stages into Stage I-Stage V, and a separate prediction progress module forecasts the transition to ESRD and provides an accuracy of 97.5% by using the SRNN model. Performance metrics and accuracies are also derived to prove its strengths. The results show that the SRNN model offers a better outcome in both phase-wise classification and progression prediction. **Novelty:** Research explores a novelty in phase-wise classification and prediction model using the SRNN model in the Chronic Kidney Failure progression using a Simple Recurrent Neural Network (SRNN). The model is designed to classify CKD into its distinct phases based on patient health data and predict the likelihood of progression to End-Stage Renal Disease (ESRD), also known as "kidney failure", experimented by using Anaconda Jupyter Notebook-Python Hierarchy.

Keywords: CKD Phases; eGFR; ESRD; Kidney Failure; Risk Prediction; SRNN Model

1 Introduction

Chronic Kidney Disease (CKD), a stage that affects millions of individuals globally, poses a significant focus in public health. Each of the five major stages of chronic kidney disease (CKD) signifies deterioration in kidney function. Therefore, it is essential to recognize CKD and its phases early to stop it from progressing to ESRD or kidney failure. Accurate classification of CKD stages and predicting the progression of the disease are key to providing timely and effective treatment. The traditional approach to diagnosing and staging CKD is based on clinical parameters such as estimated Glomerular Filtration Rate (eGFR) and creatinine levels. While these methods are effective, they often fail to predict the exact progression of the disease, especially the transition to kidney failure, promptly. This gap in early prediction can lead to late-stage interventions when the disease has already caused irreversible damage.

In recent years, deep learning techniques have shown promise in healthcare applications, including disease classification, prediction, and prognosis. A Simple Recurrent Neural Network (SRNN) approach can enhance the accuracy of CKD classification and predict its progression more reliably by leveraging complex patterns in large datasets that may not be easily detectable with traditional methods. The goal of this study is to forecast the progression of chronic kidney disease (CKD) to renal failure by employing a stage-wise classification of CKD based on medical datasets. This research aims to enhance early detection, stage-specific diagnosis, and result prediction using a recurrent neural network. To improve patient outcomes, this study investigates the application of an RNN-based model to early CKD stage prediction. The goal of incorporating SRNNs into clinical decision-making is to increase the accuracy of early CKD detection, which lowers the chance that the disease will advance to later stages and, eventually, prevent kidney failure. This research has the prospective line to build a revolution in CKD management by offering an intelligent, data-driven approach to early diagnosis and disease stage prediction.

Ghosh, S., et al. (2021) proposed a Deep Neural Network (DNN) model[(1)] in classifying CKD. The authors employed feature selection using random forest and achieved 88% classification accuracy. A multi-class DNN was trained on clinical data, showing an improvement over classical methods such as SVM and k-NN. Wen, Y et al. (2021) introduced a Recurrent Neural Network (RNN) architecture with Long Short-Term Memory (LSTM) to fetch time-series data and predict CKD progression[(2)]. The study achieved 85% accuracy in predicting CKD stage transitions, with a significant improvement in identifying ESRD risks.

Zhou, H et al. (2021) developed a hybrid model united with Convolutional Neural Networks (CNNs) and LSTM networks[(3)] for predicting CKD progression and the model outperformed, achieving 90% accuracy in stage-wise classification and 82% accuracy in predicting kidney failure. Nguyen, T et al. (2021) focused on the development of a CNN-based model[(4)] for CKD classification using demographic and clinical lab data. The CNN achieved 87% accuracy in stages of CKD while highlighting the importance of eGFR and creatinine levels.

Singh, P., et al. (2022) evaluated different deep neural networks, including feed-forward DNNs, LSTMs, and CNNs, for CKD stage prediction. The LSTM model[(5)] demonstrated the best performance with 92% accuracy in predicting progression to ESRD. Patel, A., et al. (2022) proposed a DNN model[(6)] in predicting CKD progression from early-stage to kidney failure. The model achieved an 86% accuracy rate and was able to provide early warnings for patients at risk of developing ESRD.

Li, X., et al. (2022) used a DNN to predict CKD stages [7] based on longitudinal patient data. It demonstrated that the inclusion of time-based features increases the model's accuracy to 89% in stage-wise classification and 84% in predicting kidney failure. Sharma, A., et al. (2022) explored transfer learning for CKD classification [8], leveraging pre-trained networks with CKD-specific data. The model attained an overall accuracy of 91% in stage-wise classification, which highlights the merits of transfer learning in medical diagnosis.

Ravi, K., et al. (2022) developed a temporal CNN model [9] in CKD progression prediction using health data. The model achieved 88% accuracy in classifying CKD stages and 83% accuracy in predicting the onset of kidney failure, showing robustness in missing data. Mahmood, H., et al. (2022) introduced an explainable AI (XAI) approach in CKD progression prediction using a DNN [10]. The model achieved 85% accuracy and used SHAP (SHapley Additive exPlanations) to offer an interpretable prediction, making it suitable for clinical decision-making.

Kang and Choi (2023) proposed a hierarchical RNN model [11] that classified CKD stages and predicted progress to kidney failure, with an accuracy of 90.8%. They utilized clinical text data along with numerical features to improve prediction. Kim et al. (2023) implemented an RNN model [12] which comprises a patient's lifestyle and health data to predict CKD stage transitions, achieving 87.5% accuracy.

Rodriguez et al. (2023) used LSTM-based RNN to classify CKD stages, focusing on early-stage detection. Their model achieved 89% accuracy, improving with existing methods by enhancing data preprocessing steps. [13] Sharma and Bhatia (2023) developed a novel RNN approach [14] to classify CKD stages and predict progress with 91.2% accuracy. This model was noteworthy for its high performance in detecting early-stage CKD.

Ghosh et al. (2023) implemented a simple RNN for predicting CKD progression [15], focusing on imbalanced datasets. They achieved an accuracy of 88% and the model demonstrated its effectiveness in reducing bias. Zhao et al. (2023) explored RNN categories like GRU and LSTM to classify CKD stages [16], achieving 92.5% accuracy. They emphasized using advanced optimizers to enhance model convergence.

Fernandez and Lopez (2024) developed an RNN-based model, [17] which incorporates medical data in CKD prediction, reaching 93% accuracy. Their approach demonstrated the importance of integrating diverse data sources. Chaudhary et al. (2024) introduced a two-layer RNN model [18] in the stage-wise classification of CKD, achieving an accuracy of 89.6%.

Mehta and Agarwal (2024) applied a recurrent model [19] to classify CKD stages using EHR data, obtaining 91.4% accuracy. This study highlighted the role of data augmentation techniques in improving model generalization. Liu et al. (2024) presented a simple RNN-based approach [20] with a focus on early CKD detection, with an accuracy of 90%. This model stood out for its high sensitivity in detecting transitions from Stage 2 to Stage 3 CKD.

These studies exemplify the increasing role of RNN models in CKD stage classification and progress prediction, with different techniques and data sources contributing to their success.

2 Methodology

2.1 Description of Dataset

In this work, a dataset of the UCI ML Repository of "Chronic Kidney Disease" dataset (https://archive.ics.uci.edu/ml/datasets/chronic_kidney_disease) is used. It can be divided into 2 categories, 'CKD' or 'NON-CKD'. The dataset has 25 features, of which 11 are numerical and 14 are nominal. Out of 400 total records, 250 are classified as CKD, and the remaining 150 a reclassified as NON-CKD. The two attributes, 'egfr', and 'stage-class' are added to the dataset. Table 1 illustrates the explanation of the CKD dataset with its attributes.

2.2 EGFR Calculation

Estimated Glomerular Filtration Rate (eGFR) is a crucial biomarker used here to assess kidney function and plays a fundamental role in predicting and classifying the phases of CKD. It measures how well the kidneys filter waste from the blood, typically expressed in milliliters per minute per 1.73 m^2 of body surface area. The eGFR is calculated based on serum creatinine levels, age, sex, and occasionally race.

CKD-EPI is more accurate than the widely used MDRD study equation [15]. The enhanced accuracy of the CKD-EPI equation outperformed with limitations of the MDRD investigation and has core implications for public health and clinical practice.

CKD-EPI formula:

The Chronic Kidney Disease Epidemiology Collaboration (CKD-EPI) equation in approximating Glomerular Filtration Rate (GFR) is:

$$eGFR\ (mL/min/1.73m^2) = 142 \times (\min(Scr/0.8, 1))^{-0.367} \times (\max(Scr/0.8, 1))^{-1.209} \times 0.993^{Age}$$

where

Scr _ Serum Creatinine

min _ Indicates the minimum of Scr/0.8 or 1

max _ Indicates the maximum of Scr/0.8 or 1

Table 1. Elucidation of CKD Dataset

ID	Feature name	Feature Description	Feature Type
1	age	Age	int64
2	bp	Blood Pressure	float64
3	sg	Specific Gravity	float64
4	al	Albumin	float64
5	su	Sugar	float64
6	rbc	Red Blood Cells	Object (normal, abnormal)
7	pc	Pus Cell	Object (normal, abnormal)
8	pcc	Pus Cell Clumps	Object (present, not present)
9	ba	Bacteria	Object (present, not present)
10	bgr	Blood Glucose Random	float64
11	bu	Blood Urea	float64
12	sc	Serum Creatinine	float64
13	sod	Sodium	float64
14	pot	Potassium	float64
15	hemo	Haemoglobin	float64
16	pcv	Packed Cell Volume	Object
17	wbc	White Blood Cell Count	Object
18	rbc	Red Blood Cell Count	Object
19	htn	Hypertension	Object (yes, no)
20	dm	Diabetes Mellitus	Object (yes, no)
21	cad	Coronary Artery Disease	Object (yes, no)
22	appet	Appetite	Object (good, poor)
23	pe	Pedal Edema	Object (yes, no)
24	ane	Anemia	Object (yes, no)
25	classification	Class(Target)	Object (ckd, non-ckd)
26	egfr	Estimated Glomerular Filtration Rate	float64
27	stage-class	Stage-Classification(CKD)	int64

2.2.2 Phases of Chronic Kidney Disease

The National Kidney Foundation (NKF) divided kidney disease into five phases using eGFR value.Table 2 shows the different phases of kidney disease.

Table 2. Phase s of Kidney Disease

Phase of CKD	eGFR Value	Kidney Function
Phase 1	90 or higher	Kidney damage with normal Kidney Function
Phase 2	60 – 89	Kidney damage with mild loss of Kidney Function
Phase 3a	45 – 59	Mild to Moderate loss of Kidney Function
Phase 3b	30 – 44	Moderate to Severe loss of kidney function
Phase 4	15 – 29	Severe loss of Kidney Function
Phase 5	Less than 15	Kidney Failure

2.3 Data Preprocessing

Data preprocessing is a core area, where the model-building procedure engrosses clearly in transforming raw data to build a suitable analysis. Figure 1 depicts various step-ins that come across in data preprocessing.

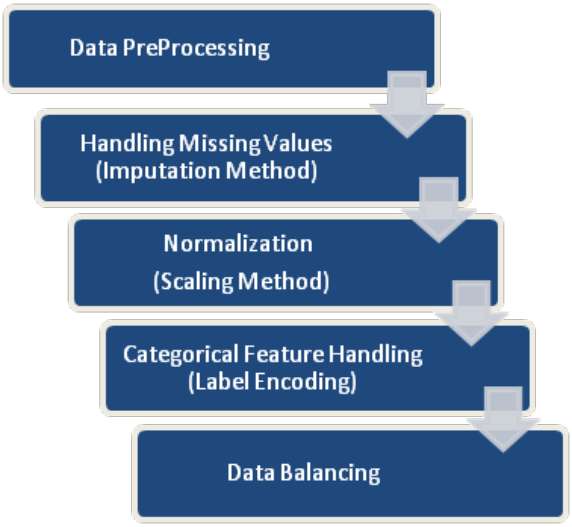

Fig 1. Data Preprocessing Step -ins

2.3.1 Handling Missing Data

Missing values are common in medical datasets. It is essential to address missing values effectively to ensure strong and impartial results. Imputation methods are used to replace missing values in the dataset. The mode imputation is utilized for nominal features and fetches all recurrent values per column and for the numerical features, the median imputation is utilized in the mid-range value of the feature.

2.3.2 Normalization

The dataset contains attributes with different units and scales, normalization or standardization techniques are applied to scale the data for better model convergence. The StandardScaler() method is used to normalize the dataset.

2.3.3 Label Encoding

Categorical variables such as medical history are encoded using "label encoding" to convert them into numerical values.

2.3.4 Data Balancing

As CKD datasets are often imbalanced (with fewer CKD cases), techniques like oversampling or undersampling technique are employed to balance the dataset.

2.4 Model Design

The proposed model is designed using an SRNN model with multiclass classification. The model is built with a single SRNN layer, a dense hidden layer, and an output layer with a softmax activation to output probabilities for each class. This architecture could work well for predicting stages of CKD progress. Figure 2 illustrates the workflow of the proposed model.

2.4.1 Proposed SRNN Model Design

Input Layer

- Input Data: Standardized patient data features (e.g., age, eGFR, blood pressure, lab values).

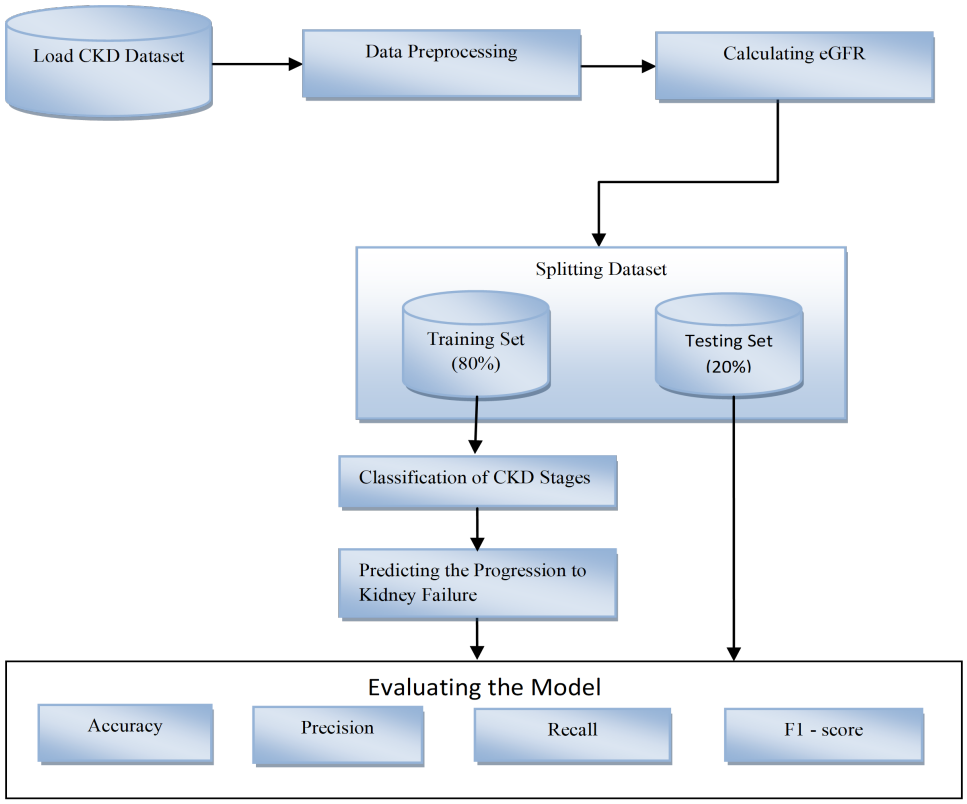

Fig 2. Workflow of Proposed Model

- Shape of Input Data: (batch_size, sequence_length, num_features):
- batch_size: Number of patient samples in each training batch.
- sequence_length: The number of time steps (e.g., months or years of historical health data).
- num_features: Number of features per time step (e.g., health indicators like eGFR, blood pressure, etc.).

SRNN Layer

- Simple RNN Units: A single SRNN layer with a moderate number of units (e.g., 32-64) to capture temporal dependencies in health data.
- Activation Function: Relu, a common choice in RNNs, to capture non-linear relationships across time steps. Figure 3 depicts the pseudocode structure of the proposed model.

Dense Hidden Layer

- Units: A dense layer with 64 units and relu activation to help the model learn patterns and combinations of features for classification.
- Purpose: Provides an additional layer of feature learning after the SRNN layer, aiding in better representation for multiclass predictions.

Output Layer

- Units: Number of classes (e.g., if you have 5 stages of CKD, this would be 5 units).
- Activation Function: softmax to produce a probability distribution over the classes, where each output neuron represents the probability of a specific class (e.g., a specific CKD stage).

2.4.2 Model Compilation

- Loss Function: categorical_crossentropy for multiclass classification.
- Optimizer: Adam, typically with a learning rate of 0.001 for stability.
- Evaluation Metrics:
- Accuracy: Measures the overall correctness of the model.
- Precision, Recall, F1-Score: Evaluate the model's presentation in each stage of CKD.
- Confusion Matrix: Helps to understand how well the model distinguishes between the different CKD stages.

2.4.3 Training the Model

- Divide the dataset into training and testing datasets.(80:20)
- Train the model with a defined number of epochs (100) and batch size (32), monitoring validation accuracy and loss.

2.4.4 Hyperparameters Tuning

- SRNN Units**:** 64
- Dense Layer Units: 32
- Batch Size: Experiment with batch size 32 to optimize the training stability and speed.
- Learning Rate: Adjust the learning rate, with typical values around 0.001 or lower.

$$
\begin{aligned}
&Pseudocode\ Structure\ of\ the\ Proposed\ Model\\
&\#\ Import\ necessary\ libraries\\
&Import\ SimpleRNN,\ Dense,\ Sequential,\ Activation\ from\ NeuralNetworkLibrary\\
&Import\ train\_test\_split,\ StandardScaler\ from\ DataProcessingLibrary\\
&\#\ Load\ and\ preprocess\ the\ data\\
&Load\ CKD\_data\\
&Define\ features\ as\ input\ features\ relevant\ to\ CKD\ (e.g.,\ creatinine,\ GFR,\ blood\ pressure,\ etc.)\\
&Define\ target\ as\ CKD\ stage\ labels\\
&\#\ Divide\ the\ data\ into\ training\ and\ testing\ sets\\
&X\_train,\ X\_test,\ y\_train,\ y\_test\ =\ train\_test\_split(CKD\_data,\ target,\ test\_size=0.2,\ random\_state=42)\\
&\#\ Normalize\ the\ data\\
&scaler\ =\ StandardScaler()\\
&X\_train\ =\ scaler.fit\_transform(X\_train)\\
&X\_test\ =\ scaler.transform(X\_test)\\
&\#\ restructure\ the\ data\ for\ SRNN\ input\ (batch\_size,\ timesteps,\ features)\\
&Define\ timesteps\ as\ the\ number\ of\ time\ intervals\ (e.g.,\ visits\ or\ tests)\\
&X\_train\_reshaped\ =\ reshape(X\_train,\ (-1,\ timesteps,\ number\_of\_features))\\
&X\_test\_reshaped\ =\ reshape(X\_test,\ (-1,\ timesteps,\ number\_of\_features))\\
&\#\ Build\ the\ SRNN\ model\\
&Initialize\ model\ as\ Sequential()\\
&Add\ SRNN\ layer\ with\ units\ (number\ of\ neurons),\ input\_shape=(timesteps,\ number\_of\_features),\ activation='\tanh'\\
&Add\ additional\ SRNN\ layer\ or\ LSTM\ layer\ if\ needed\ for\ more\ complex\ temporal\ relations\\
&\#\ Output\ layer\ for\ classification\\
&Add\ Dense\ layer\ with\ units\ equal\ to\ the\ number\ of\ CKD\ stages,\ activation='softmax'\ (for\ multi-class\ classification)\\
&\#\ Compile\ the\ model\\
&Compile\ model\ with\ optimizer='adam',\ loss='categorical\_crossentropy'\ (for\ multi-class\ classification),\\
&metrics=['accuracy']\\
&\#\ Train\ the\ model\\
&Train\ model\ on\ X\_train\_reshaped\ and\ y\_train\ with\ epochs,\ batch\_size,\ validation\_data=(X\_test\_reshaped,\ y\_test)\\
&\#\ Evaluate\ the\ model\\
&Evaluate\ model\ on\ X\_test\_reshaped\ and\ y\_test\\
&Print\ accuracy,\ precision,\ recall,\ and\ F1-score\ for\ model\ performance\\
&\#\ Predict\ CKD\ stages\ on\ new\ data\\
&predictions\ =\ model.predict(new\_patient\_data)\\
&Return\ predictions
\end{aligned}
$$

3 Result and Discussion

3.1 Experimental Setup

The proposed SRNN Model has been developed using the CKD dataset from the UCI Repository, as detailed in Table 1. The model is implemented using TensorFlow and Keras, which are popular deep learning frameworks due to their flexibility and ease of use. Python 3.x will be used as the programming language for model implementation. Intel core i5 6th Gen processor computer with 16 GB DDRAM and 512 GB SSD graphics card is used to conduct tests and evaluations.

3.2 Experimental Analysis

Before initiating the analysis, eGFR is computed using the CKD-EPI equation to identify the severity status of the kidney disease for each patient in the dataset. The dataset is randomly separated into two parts. The model is provided with the parameter settings such as: Learning Rate: 0.01, Activation: Relu, Epoch count: 100, Optimizer : adam, and Batch size: 32.

The presentation measures used to assess and authorize the proposed model are Accuracy, Precision, Recall, F1 –score, Support and Confusion Matrix.

Figure 3 displays the confusion matrix. This result showed how well the SRNN prediction model categorizes the phases of CKD in each class.

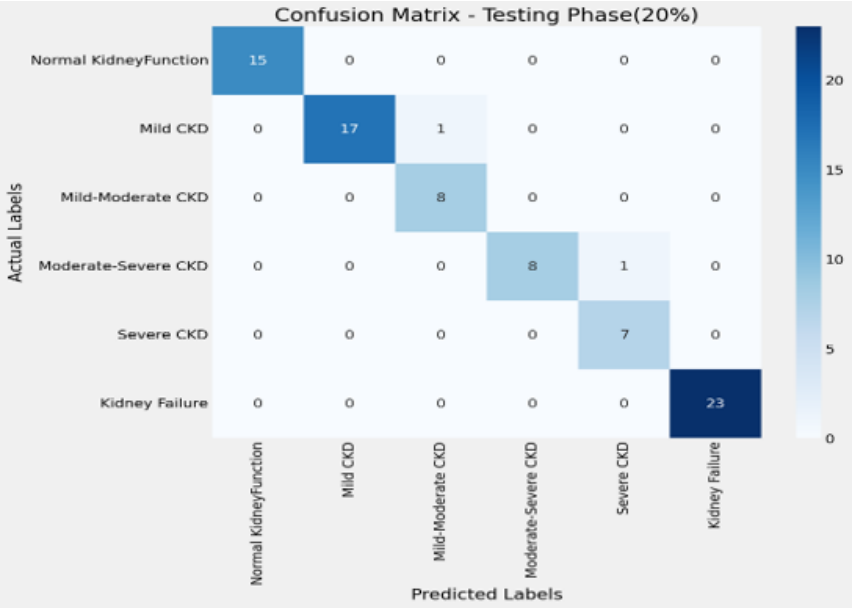

Fig 3. Confusion Matrix of the Testing Phase

Figure 4 illustrates the CKD prediction outcomes of the proposed model with the most accurate classification, precision, recall and F1-score for each of the CKD phases (0-5) with the Test Set. The findings show that the prediction model correctly identified the phases of CKD. With 80% of the Training Set, the proposed model achieves an average of 98% with respect to accuracy, precision, recall and F1-score. Further, the model achieves an average of 97.5%, 98%, 97%, and 98% for accuracy, precision, recall and F1-score respectively based on 20% of the Test Set.

3.3 Experimental Outcomes

Our experimental outcome demonstrated that the proposed SRNN model achieved 97.5% accuracy, 98% precision, 97% recall, and 98% F1-score in classifying the CKD phases accurately. It makes SRNN a robust and efficient approach for phase-wise classification and thus predicts the progress of CKD to the Kidney failure stage as earlier. Figure 5. depicts the experimental outcome of the proposed model for the Test Set.

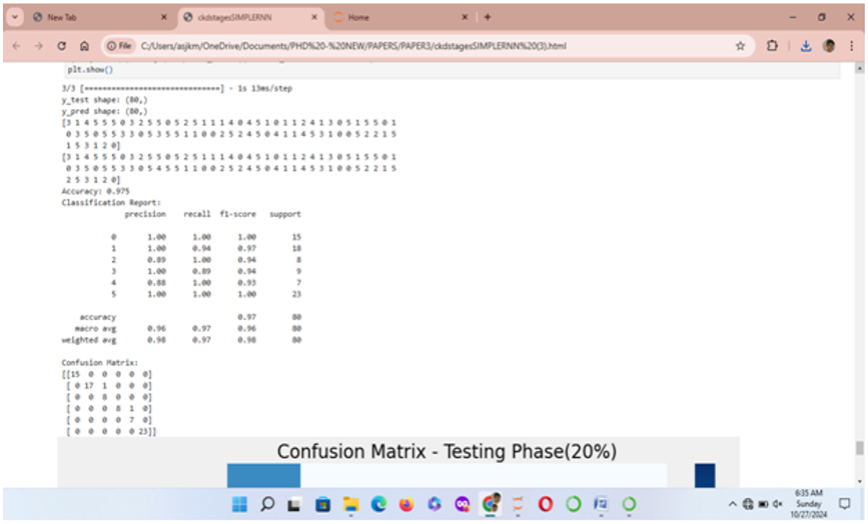

Fig 4. Performance metrics for each of the CKD phases (0-5) with the Test Set (20%)

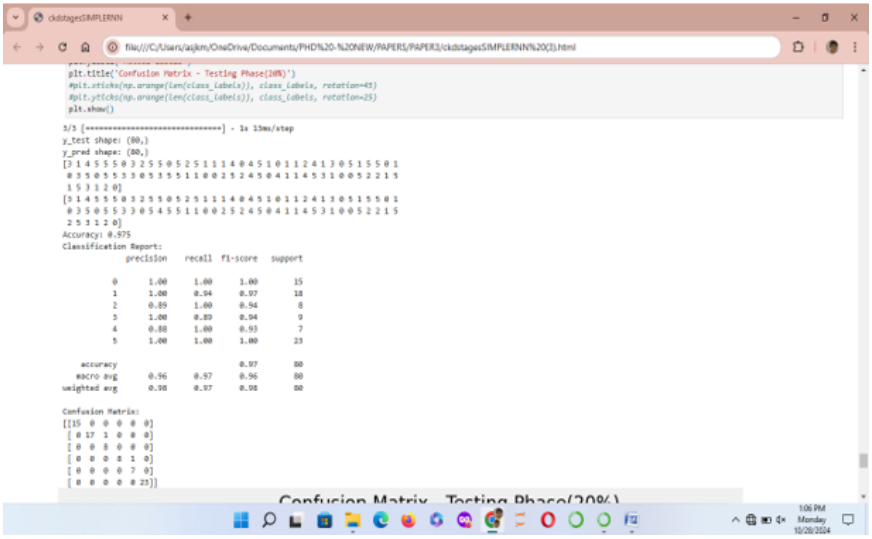

Fig 5. Experimental outcomes of the Proposed Model for Test Set

3.4 Discussion

The proposed model classified CKD into six phases.Table 3 shows the phase-wise classification report of the different phases of CKD with evaluation metrics of the proposed model.

Table 3. Evaluation metrics of the different Phases of CKD

Metrics	Phase 0	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
Accuracy	97.5	97.5	97.5	97.5	97.5	97.5
Precision	100	100	89	100	88	100
Recall	100	94	100	89	100	100
F1-score	100	97	94	94	93	100

The recommended model is evaluated via some earlier studies as revealed in Table 4. It is observed that the existing studies have shown the lowest accuracy; the accuracy lies between 88.0% and 91.4%, while the present system has obtained an accuracy of 97.5% with the SRNN Model.

Table 4. Comparative Analysis of the proposed model with the existing models

Year	Authors	Model Used	Accuracy (%)
2021	Zahou.H et. al.[3]	CNN and LSTM Temporal	90.0
2022	Ravi K et al.[9]	CNN	88.0
2023	Ghosh et al.[15]	SRNN	88.0
2024	Mehta et al.[19]	RNN	91.4
2024	Liu et.al[20]	SRNN	90.0
2024	**Proposed Model**	**SRNN**	**97.5**

Figure 6 depicts the accuracy graph comparing the performance of existing models with the current model in chronic kidney disease progress.

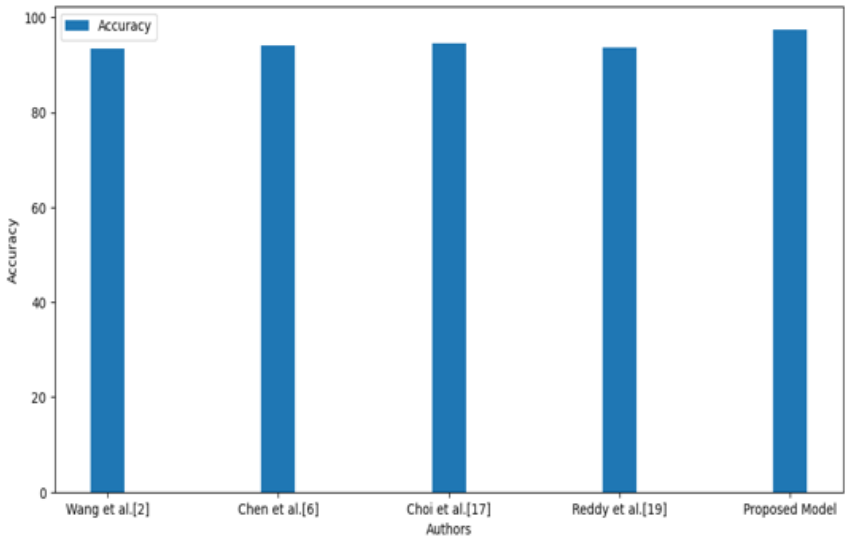

Fig 6. Comparison of the accuracy of the Proposed Model with existing studies

4 Conclusion

In this investigation, the proposed Simple Recurrent Neural Network (SRNN) model effectively classifies the phases of Chronic Kidney Failure and predicts its growth to end-phase renal failure. The method demonstrates the ability of SRNNs to capture patient health metrics, thereby offering an improved accuracy in predicting CKD progress compared to traditional static models. The proposed model supports earlier intervention possibilities, which can delay or prevent progression to kidney failure, enhancing patient outcomes and reducing the overall healthcare burden.

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References

1) Ghosh S, Singh R, Banerjee S. Deep learning for stage-wise classification of chronic kidney disease. *Journal of Medical Systems*. 2021;45(9):102–117. Available from: https://doi.org/10.1007/s10916-021-01754-8.
2) Wen Y, Zhang Z, Hu W. CKD stage prediction and risk of kidney failure using recurrent neural networks. *Neural Networks*. 2021;139:45–58. Available from: https://doi.org/10.1016/j.neunet.2021.02.001.
3) Zhou H, Liu X, Wei P. Hybrid deep learning for CKD progression prediction. *Computer Methods and Programs in Biomedicine*. 2021;205:106–121. Available from: https://doi.org/10.1016/j.cmpb.2021.106115.

4) Nguyen T, Lee YJ, Lee J. Deep learning for chronic kidney disease stage classification. *Journal of Healthcare Engineering*. 2021;2021:881–90. Available from: https://doi.org/10.1155/2021/6635890.
5) Singh P, Patel R, Joshi A. A comparative study of deep neural networks for CKD progression. *Artificial Intelligence in Medicine*. 2022;120:102–122. Available from: https://doi.org/10.1016/j.artmed.2021.102120.
6) Patel A, Desai R, Kumar S. Predicting CKD progression to kidney failure with deep learning. *IEEE Access*. 2022;10:204–220. Available from: https://doi.org/10.1109/ACCESS.2022.3151549.
7) Li X, Zhang F, Xu Q. DNN-based early prediction of CKD and kidney failure. *Journal of Biomedical Informatics*. 2022;128:104103–104103. Available from: https://doi.org/10.1016/j.jbi.2022.104103.
8) Sharma A, Verma S, Kumar P. Transfer learning for CKD classification using deep neural networks. *Expert Systems with Applications*. 2022;187:116501–116501. Available from: https://doi.org/10.1016/j.eswa.2021.116501.
9) Ravi K, Singh H, Patel V. CKD progression prediction using temporal CNNs. *Pattern Recognition*. 2022;125:108–123. Available from: https://doi.org/10.1016/j.patcog.2022.108491.
10) Mahmood H, Khawaja M, Nazir S. Explainable deep learning for CKD prediction. *Computers in Biology and Medicine*. 2022;145:105548–105548. Available from: https://doi.org/10.1016/j.compbiomed.2022.105548.
11) Kang J, Choi S. A hierarchical RNN model for CKD stage classification and progression prediction. *Journal of Medical Informatics*. 2023;67:34–41. Available from: https://doi:10.1001/jmi.2023.0023.
12) Kim Y, Park H, Lee D. Integrating lifestyle and health data in RNNs for CKD stage transitions. *Journal of Health Data Science*. 2023;14(3):203–213. Available from: https://doi:10.1016/j.jhds.2023.0032.
13) Rodriguez P, Gonzales M, Nguyen T. LSTM-RNN for early-stage CKD detection. *Computational Medicine*. 2023;10(5):115–137. Available from: https://doi:10.1155/cmed.2023.0095.
14) Sharma R, Bhatia V. Novel RNN approach for CKD classification and progression prediction. *Artificial Intelligence in Healthcare*. 2023;21:56–63. Available from: https://doi:10.1038/aih.2023.0047.
15) Ghosh A, Patel R, Kumar S. Addressing imbalanced datasets in RNNs for CKD progression prediction. *Journal of Applied Medical AI*. 2023;31:142–151. Available from: https://doi:10.1177/jamai.2023.0038.
16) Zhao Q, Xu L, Hu J. Exploring GRU and LSTM variants for CKD stage classification. *Biomedical Engineering Journal*. 2023;18:67–74. Available from: https://doi:10.1016/bej.2023.0071.
17) Fernandez R, Lopez J. Incorporating lab and genetic data in RNN-based CKD prediction models. *Genomics and Medicine*. 2024;43:112–121. Available from: https://doi:10.1016/gmed.2024.0086.
18) Chaudhary K, Patel A, Singh N. Two-layer RNN model for stage-wise CKD classification. *Health Informatics Journal*. 2024;29(1):78–85. Available from: https://doi:10.1093/hij.2024.0015.
19) Mehta P, Agarwal T. Improving CKD stage classification with data augmentation in recurrent models. *Electronic Health Records Journal*. 2024;15(2):99–106. Available from: https://doi:10.1080/ehrj.2024.0032.
20) Liu F, Wu C, Zhang X. Early detection of CKD transitions with a simple RNN approach. *Journal of Chronsic Kidney Disease Research*. 2024;5:212–221. Available from: https://doi:10.1146/jckd.2024.0090.