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Full Length Research Paper

Cloud-Enabled Autoencoder with RNN Framework for Early Detection of Chronic Kidney Disease

Andri Ulus Rahayu
Electrical Engineering,
Siliwangi University,
Indonesia
andriulusr@unsil.ac.id

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ABSTRACT
Prevention of any progression in CKD to an advanced stage necessitates the early diagnosis of the disease. This work presents the Cloud-Enabled Autoencoder with RNN Framework for Early Detection of Chronic Kidney Disease, which exploits the combined strengths of Autoencoders for feature extraction and Recurrent Neural Networks for temporal dependencies from clinical study data. This model uses historical medical data for the prediction of CKD onset, thereby instilling the notion of proactive healthcare. The framework is hosted on a cloud platform so that the scalability and accessibility of advanced functionalities are secured for healthcare professionals. Consequently, this model enhances CKD detection and timely intervention through the integration of Autoencoders for dimensionality reduction and RNNs for sequential pattern recognition, thus improving the patient's quality of care.

Keyword: *Chronic Kidney Disease (CKD), Autoencoder, Recurrent Neural Networks (RNN), Cloud Computing, Machine Learning in Healthcare, Early Detection Systems*

1 INTRODUCTION

Early identification and diagnosis of chronic kidney disease (CKD) become all the more important to prevent the progressive deterioration leading to kidney failure which is one of the foremost causes of death around the globe [1]. Conventional diagnostic means heavily depend on clinical skill and laborious evaluation of data pertaining to patients and often are time-consuming and error prone. Advancement in machine learning enables data-driven models to predict CKD outcomes accurately and more economically [2]. In this context, we offer a Cloud-Enabled Autoencoder with RNN Framework for Early Detection of Chronic Kidney Disease. This model exploits the advantages of Autoencoders (AE) in feature extraction and Recurrent Neural Networks (RNN) in modelling sequential dependencies in clinical data, both of which make it suitable for time series prediction in the healthcare domain [3]. The prime objective of the framework is to improve the detection of CKD using historical medical data to identify risk patients early for possible timely intervention. The setting uses an Autoencoder for dimensionality reduction, followed by an RNN to capture temporal dependencies which are characteristic of sequential medical data [4]. Hosted in the cloud, the trained model becomes a scalable and accessible solution for a healthcare professional to use for an efficient and accurate diagnosis of CKD. This implies that outcomes for patients can be afforded by battering their levels of proactive care through predictive insights gained from clinical data [5]. The flexibility of the framework allows for continuous improvements with the integration of additional data sources for retraining the model.

PROBLEM STATEMENT

The rapid identification and management of CKD in its early stages are vital because the disease progresses to kidney failure, which is one of the leading causes of death globally [6]. Traditional diagnostic methods often rely on clinical tests, such as serum creatinine levels, blood pressure readings, and urine analysis. However, these methods can be cumbersome, error-prone, and inefficient, leading some clinicians to question their reliability [7]. Early diagnosis of CKD becomes extremely challenging due to the limitations of these conventional approaches. To address this issue, this work proposes an automated and efficient mechanism for early CKD detection, utilizing advanced machine learning techniques [8]. The project aims to develop a Cloud-Enabled Autoencoder with a Recurrent Neural Network (RNN) framework, specifically

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designed for the early detection of CKD. The Autoencoder will be responsible for feature extraction, allowing the system to identify relevant patterns from medical data [9]. The RNN will then model temporal dependencies in sequential medical data, enabling accurate predictions over time. The combination of Autoencoder and RNN is expected to improve the accuracy of predictions by capturing both feature and temporal dependencies in the data [10]. The system will be cloud-enabled, allowing for easy access and scalability in real-world healthcare applications. By leveraging these state-of-the-art techniques, the proposed system will automate the detection process, reducing human error and enhancing diagnostic efficiency [11]. The ultimate goal is to create a tool that can be easily integrated into clinical settings to facilitate early detection and timely management of CKD. This approach will significantly improve patient outcomes by enabling earlier interventions and reducing the burden on healthcare systems [12]. In conclusion, the use of machine learning in CKD detection represents a promising step toward more efficient and accurate healthcare solutions. The integration of Autoencoders and RNNs offers a novel method for tackling a critical healthcare challenge. The proposed framework has the potential to revolutionize CKD diagnosis and management through automation and advanced data processing capabilities [13].

Objective

- Investigate how the Autoencoder's working is beneficial for extracting features from high-dimensional clinical datasets and enhancing prediction of CKD onset.
- Develop an RNN-based model which should analyze the temporal dependencies in patient data i.e., when the clinical parameters change with time; presence of such temporal information will aid in predicting progression of CKD through time.
- Deploy the trained Autoencoder and RNN model on a cloud platform to ensure scalability and real-time access for healthcare professionals.
- Standard methods of model performance evaluation shall be used: accuracy, precision, sensitivity, specificity, F-measure, and NPV, in order to assess CKD diagnosis.

2. LITERATURE SURVEY

CKD was a research trend in health care regarding the early diagnosis and detection of the condition due to the progressive features of the disease and the high rate of morbidity that it has left in the patient community [14]. The old-fashioned ways are to take clinical tests including checking serum creatinine levels, blood pressure, and urine analysis for kidney function. Unfortunately, these tests may not always be able to catch CKD at an early stage and may lead to late detection. The researchers reported recently are concerned with the introduction of machine learning techniques, especially in predicting the possible outcome of CKD from previously collected clinical data. The proposed method applies encryption techniques similar to those demonstrated by Gollapalli et al. (2024), who introduced a cloud-security framework combining AES-CBC and end-to-end encryption to protect data in multi-tenant environments while reducing latency and enhancing confidentiality. Building on their findings, this approach secures cloud data for latency-sensitive applications within our specific domain, ensuring both strong security and high performance [15].

Autoencoders, a type of unsupervised neural network, have become an essential tool in machine learning for feature extraction and dimensionality reduction. By learning to compress and reconstruct data, Autoencoders identify the most relevant patterns in high-dimensional datasets, enabling models to focus on the most important features. This process helps eliminate noise and irrelevant variables, thus improving the performance of predictive models [16]. In particular, Autoencoders have shown great promise in enhancing disease prediction models, such as those used for chronic kidney disease (CKD) detection. By reducing the complexity of the data, they make it easier for machine learning models to identify meaningful patterns that might otherwise be overlooked. The ability to create a low-dimensional representation of the data allows for more accurate and efficient predictions, which is crucial in medical diagnostics where precision and reliability are paramount. Previous work has demonstrated the significant benefits Autoencoders bring to predictive healthcare models.

Deep learning, a subfield of machine learning, has recently shown immense potential in transforming biomedical and clinical applications, significantly enhancing quantification and classification workflows. One of the pioneering areas benefiting from DL is cellular morphology quantification, which plays a vital role in various healthcare applications. At its core, deep learning leverages neural networks with multiple layers to process complex data, allowing the model to learn and extract intricate patterns from large datasets [17]. This ability to handle vast amounts of information is particularly advantageous in the analysis of biological data. In embryology, DL is used to quantify cellular morphology and track developmental stages, improving understanding and diagnosis. In point-of-care ovulation testing, DL models help predict ovulation cycles with increased accuracy. Similarly, DL serves as a predictive tool in monitoring fetal heart health during pregnancy. Moreover, DL is increasingly applied in cancer

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diagnostics, where it aids in the classification of cancer histology images, providing more accurate and timely diagnoses. In the study of autosomal polycystic kidney disease and chronic kidney diseases, DL models help predict disease progression, improving early detection and treatment outcomes.

Yallamelli et al. (2023) combine AI for medical event forecasting and blockchain for secure data storage, enhancing fraud detection, billing efficiency, and system reliability in healthcare. Leveraging their findings, the proposed method integrates these technologies to optimize patient care and operational efficiency. Their success in improving healthcare processes informs the development of our own framework [18].

RNNs have gained significant attention in healthcare applications due to their ability to model sequential data effectively. These networks are particularly useful for tasks like time-based health monitoring, where the data is dependent on temporal factors. RNNs are designed to process sequences of data, making them ideal for analyzing time-series medical records, where past health information can inform future predictions [19]. By feeding historical medical data into RNNs, the models can learn patterns and relationships from previous health records, enhancing their ability to forecast future health conditions. This capability makes RNNs highly valuable for predicting the progression of chronic diseases such as chronic kidney disease (CKD). Studies have shown that RNNs outperform traditional models, especially when combined with feature extraction techniques like Autoencoders. Autoencoders help reduce the dimensionality of the data, removing noise and irrelevant features, which improves the accuracy of RNNs in making predictions. The integration of RNNs and Autoencoders, therefore, enhances predictive modeling, offering a powerful tool for early detection and monitoring of CKD progression in healthcare settings.

Cloud computing has emerged as a transformative solution for deploying machine learning models in healthcare, offering scalability and accessibility that significantly benefit health applications. Its integration into healthcare systems, particularly for chronic kidney disease (CKD) detection, has addressed a critical societal need by allowing health institutions to use cloud-based predictive models without the heavy investment in costly infrastructure. Cloud platforms enable continuous model updates and improvements by supporting real-time data processing, which enhances the accuracy and reliability of predictions over time. This capability is crucial for health monitoring systems, where timely and precise predictions can lead to better patient outcomes. Many studies have highlighted the advantages of cloud-based healthcare solutions, particularly their ability to provide real-time access to prediction models and decision-support systems [20]. Such systems enable healthcare providers to make data-driven decisions quickly, improving patient care and potentially reducing medical errors. By offering a flexible and cost-effective approach to model deployment, cloud computing has become an essential tool in modernizing healthcare services and improving patient outcomes, especially in chronic disease management.

Diabetes is a chronic condition caused by inefficient insulin use in the body. Early detection can significantly improve patients' quality of life. Unlike traditional methods, deep learning models eliminate the need for manual feature extraction. In this study, we developed a real-time monitoring hybrid deep learning model to detect and predict Type 2 diabetes mellitus, utilizing the publicly available PIMA Indian diabetes database. The study contributes in four ways [21]. First, it conducts a comparative analysis of various deep learning models for diabetes detection. Based on experimental results, we propose merging two models CNN (Convolutional Neural Network) and Bi-LSTM (Bidirectional Long Short-Term Memory) to enhance diabetes prediction accuracy. Our findings show that the CNN-Bi-LSTM model outperforms other deep learning techniques, achieving an accuracy of 98%, sensitivity of 97%, and specificity of 98%, which is 1.1% higher than existing state-of-the-art algorithms. This hybrid model provides clinicians with real-time monitoring capabilities and comprehensive patient data for improved care and decision-making

AI’s impact in radiology is evident through the use of CNNs for image processing and VAEs for data augmentation and privacy protection, highlighting challenges such as data privacy and the need for large datasets, as discussed by Sitaraman (2022). Leveraging these findings, the proposed method integrates similar AI techniques to improve early detection in healthcare while addressing both ethical and technical constraints [22].

Blockchain technology, gaining significant momentum in the digital era, is expanding its application far beyond cryptocurrencies. In healthcare, it enhances data-sharing, allowing users to control access to their Electronic Health Records (EHRs) based on user type, ensuring privacy and security [23]. The integration of blockchain with machine learning combines the strengths of both technologies data analysis and prediction with robust security enabling predictions from authentic datasets without compromising integrity. In this paper, the focus is on predicting diabetic retinopathy (DR), a chronic condition caused by diabetes that leads to blindness. The dataset, sourced from IEEE Data Port, underwent pre-processing using median filtering and lesion segmentation. The Taylor African Vulture Optimization (AVO) algorithm was

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employed for hyper-parameter tuning, with the significant features then passed to the SqueezeNet classifier for prediction. The prediction results were stored in blockchain architecture, ensuring secure, authorized access by the EHR manager. The proposed model outperformed previous approaches, achieving 94.2% accuracy, 94.8% sensitivity, and 93.4% specificity.

Transplant pathology is crucial for ensuring the proper function of transplanted organs and preventing immune rejection. Accurate diagnosis and timely treatment are essential for improving transplant outcomes. Recent advances in artificial intelligence (AI)-empowered digital pathology offer potential in monitoring allograft rejection and managing immunosuppressive drug weaning [24]. To explore AI's role in transplant pathology, a systematic review of electronic databases from January 2010 to April 2023 was conducted, using the PRISMA checklist for article selection. A total of 68 articles were identified, with 14 meeting the inclusion criteria. The review focuses on AI applications in four major transplant organs: heart, lungs, liver, and kidneys. Several deep learning-based AI models have been developed to analyze biopsy specimens from transplant organs, showing promise in enhancing clinicians' decision-making and reducing diagnostic variability. The review concludes that while AI has limitations, its advancements could significantly improve transplant outcomes and pave the way for future progress in this field.

Basani (2024) introduces a hybrid YOLOv3-Mask RCNN model to improve object localization in IoT-enabled RPA systems, enhancing both speed and accuracy. The model outperforms conventional methods with impressive results in dynamic environments. Based on these insights, the proposed method aims to enhance object localization and prediction accuracy in healthcare, particularly for medical imaging and diagnostics [25].

3. PROPOSED METHDOLOGY

The flow diagram for detecting CKD using a machine learning pipeline begins with the Data Collection phase, where clinical data such as patient history, lab results, and vital signs are gathered. The next step, Preprocessing, involves cleaning the data by handling missing values, normalizing features, and encoding the target variable, which in this case is the presence or absence of CKD. Once the data is preprocessed, Feature Extraction is performed using an Autoencoder (AE), a type of unsupervised machine learning model that reduces the dimensionality of the data and identifies relevant features that contribute to CKD prediction [26]. These extracted features are then passed on to the Classification step, where a Recurrent Neural Network (RNN) model is trained to predict the outcome of CKD based on the available features. The Training phase involves optimizing the RNN model by feeding it the extracted features, allowing the network to learn patterns in the data. After training, the model undergoes Validation using Performance Metrics such as accuracy, precision, and recall to assess how well it can predict CKD outcomes on unseen data. If the model meets the required accuracy, it is then Deployed in the Cloud, enabling it to be accessed remotely and providing scalability for real-world applications. With the model deployed, it can predict outcomes for new, incoming data, providing clinicians with valuable support for early CKD detection. By leveraging this cloud-based solution, healthcare providers can access and utilize the model as part of their diagnostic workflow, improving efficiency and reducing human error. Overall, this machine learning pipeline aims to enhance the accuracy and scalability of CKD detection through automated and data-driven predictions [27].

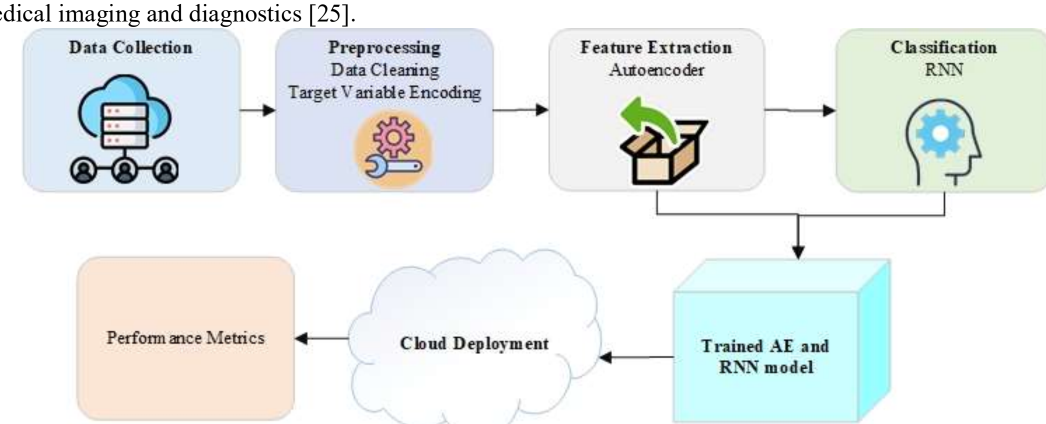

Figure 1: CKD Detection Using Autoencoder and RNN

3.1 Data collection

The database consists of clinical records containing different attributes of patients suffering from CKD. The parameters included are blood cell counts; blood pressure; serum creatinine; blood urea; glucose levels; and other related diagnostic

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measures. The dependent variable is referred to as presence of CKD or absence of CKD. These many findings are gathered from health-relevant points of the numerous conditions of CKD. The data set is preprocessed for the missing values and the non-numeric attributes are encoded to maintain the consistencies. This cleaned data set will be used after training for model prediction. A cybersecurity monitoring approach using Graph Neural Networks (GNNs) and semantic stream processing has been shown to reduce false positives by 37% while achieving high precision (94.3%) and maintaining low latency. Building on these capabilities, the proposed method adopts similar techniques to strengthen real-time fraud detection and enhance prediction accuracy, extending these concepts to improve healthcare systems particularly in the diagnosis of chronic kidney disease based on the findings of Induru and Arulkumaran (2021) [28].

3.2 Preprocessing

To begin, missing values are to be handled by dropping rows that have NaNs, since that is what the project says. Numeric features should then become float types ensuring its defined in the machine learning model. Then, the entire dataset would then be standardized using StandardScaler making all the features in common, so it will be better in using next models like PCA, Autoencoders, and RNNs. Categorical attributes then undergo encoding using either Label Encoding or One-Hot Encoding, if there are any. Outliers are also treated as these might influence the model prediction [29]. Lastly, separation of the dataset prepared into features and target variable: train and test for the model.

3.2.1 Data Cleaning

Data cleaning tackles the identification and treatment of issues about the data set, such as the missing value, formatting, or inconsistency [30]. The first step involves deleting rows that contain missing values (NaNs), following the project direction that demands cleaning the dataset for information regarding the analysis. This can be represented as:

$$\text{Cleaned Data} = \text{Original Data} - \text{Rows with NaNs} \tag{1}$$

Next, numerical features are converted to the proper data type (float) and ready for machine-learning algorithms. If any outliers are detected, they are usually fixed or deleted so that they do not bias the model. Eventually, the cleaned data are homogenized and properly formatted so that all variables are standardized for further analysis and model training.

3.2.2 Target Variable Encoding

Target variable encoding is defined as encoding the target labels, CKD status in this instance, into a numerical form so they can be utilized by machine-learning models [31]. The target variable is, in this case, binary, with two values, 'ckd' for someone having CKD and 'not ckd' for a person with no CKD. These labels are encoded under Label Encoding, which assigns 1 for 'ckd' and 0 for 'not ckd.' The notation of the encoding process is:

$$\text{Encoded Target} = \begin{cases} 1 & \text{if CKD} = \text{'ckd'} \\ 0 & \text{if CKD} = \text{'notckd'} \end{cases} \tag{2}$$

This numeric representation ensures that the machine-learning model is able to interpret the information about the target variable and predict accordingly.

3.3 Feature Extraction Using Auto Encoder

The procedures involved in malleable feature-see extraction by autoencoders are lowering data dimensionality with preservation of the very salient features of data functionalities. This refers to the fact that an Autoencoder is a neural network that is specifically built to learn the compressed version (encoding) of the input data. The whole process entails two stages: the encoder compresses data into lower-dimensional representation, and the decoder reconstructs the original data from this compressed form. A hybrid approach for workload forecasting in autonomic database systems introduced by Parthasarathy (2023) combines evolutionary algorithms and clustering techniques to achieve dynamic optimization, resulting in improvements in response time, throughput, and resource utilization. Leveraging these strategies, the proposed method adapts similar techniques to enhance predictive accuracy and resource management in healthcare, particularly for early detection of chronic kidney disease [32].

3.3.1 Auto Encoder

An Autoencoder constitutes of a pair of parts: the encoder and the decoder. The encoder encodes the input X into a compact lower-dimensional representation, whereas the decoder reconstructs the original input from this representation [33]. This is illustrated mathematically as follows:

$$\hat{X} = f_{\text{decoder}}\left(f_{\text{encoder}}(X)\right) \tag{3}$$

Where, the input is called X, the encoding function f_{encoder} compressing it into a lower-dimensional space (the latent space), the decoding function f_{decoder} reconstructing input from the latent space, while $\hat{X}$ is the reconstructed data

3.4 Classification using RNN

This is a diagram of a recurrent neural network (RNN) architecture consisting of an input layer, two hidden layers, and an output layer. RNNs offer a recurrence between the layers through which the output of a given hidden layer at a given time step can be fed into the same layer during the next time step. This encourages an RNN to learn how to take

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sequential data and give relationships to information collected from earlier time periods. The input is passed to the network, propagates through its hidden layers, and then combines recurrences that uphold some previous time step's information. Finally, in this line of application area-limited tasks such as time series forecasting, natural language processing, and predicting a sequence, such information lends itself well to the output layer giving the predictions of the model according to the patterns learned. Valivarthi and Kurniadi (2024) recommend a hybrid model combining LSTM, CNN, Transformers, and spectral analysis to detect side-channel attacks in embedded systems. The model achieves 97% detection accuracy and robust real-time performance. Adapting these methods, the proposed approach applies similar hybrid techniques to enhance predictive accuracy in healthcare, particularly for early chronic kidney disease detection [34].

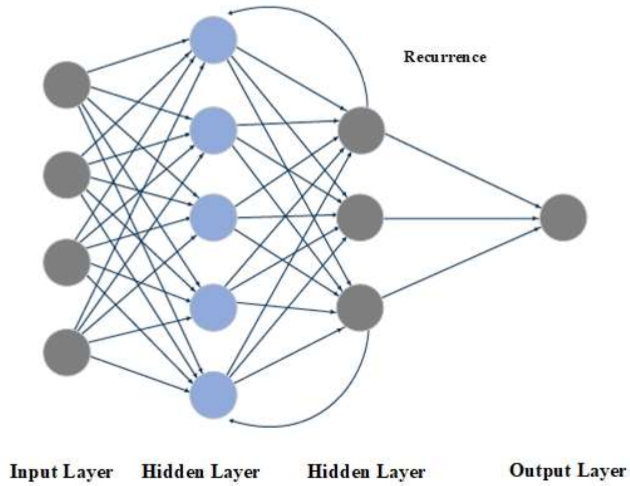

Figure 2: RNN

3.4.1 Input Layer

The raw incoming sequence data during each time-step, designated as the input layer X_t, is fed into the input usually by a vector that collectively represents all features of data collected during particular time t [35]. This might be any kind of features, like time-series values, words in a sentence, or even readings from sensors. The data is forwarded through the input layer to the next hidden layers. For example, the input might comprise the following at current time step t:

$$X_t = [x_1, x_2, \dots, x_n] \tag{4}$$

where $x_1, x_2, \dots, x_n$ are individual features of the input at time t. This data then becomes forwarded to hidden layers in processing.

3.4.2 Hidden Layer

Even the present input X_t and the old hidden state, h_{t-1} are processed through the hidden layer in an RNN. The purpose of this layer is to learn important dependency of the data temporally by recalling past inputs. Here, the hidden state at time step t, h_t, is calculated from the below equation:

$$h_t = f(W_{hh}h_{t-1} + W_{xh}X_t + b_h) \tag{5}$$

Where, W_{hh} is the weight matrix connecting the previous hidden state to the current hidden state. W_{xh} is the weight matrix connecting the input at time step t to the hidden state. b_h is the bias term for the hidden layer. f is the activation function, generally tanh or ReLU, which introduces non-linearity to the model.

3.4.3 Recurrence

RNN allows sequence data processing due to recurrences. At time step t hidden state h_t is dependent on previous hidden state h_{t-1}. In this way, network could "remember" the past and use the information for providing current state inputs. Mathematically, this recurrence is the previous hidden state being used as part of the current one in the computation of the current hidden state. A healthcare system integrating lightweight CNNs, capsule networks, and a DAG-based blockchain has been shown to improve diagnostic accuracy, scalability, and data security, achieving 99.9% data integrity, 96.4% accuracy, and 97.1% sensitivity performance well-suited for resource-constrained environments. Building on these advancements, the proposed method applies similar technologies to strengthen early CKD detection and enhance data security, as demonstrated by Nippatla et al. (2024) [36].

$$h_t = f(W_{hh}h_{t-1} + W_{xh}X_t + b_h) \tag{6}$$

It is this recurrent connection that makes RNNs substantively different from their standard, feed-forward neural-network cousins. This provision over time for the hidden state makes an RNN capable of handling sequential data and catching patterns that cross time steps.

3.4.4 Output Layer

The output layer is referred to as the layer that makes predictions using the information fed to it through the hidden layers. The output y_t at every time t is determined by the manipulation of hidden state h_t according to the weight matrix W_{hy} with an added bias term b_y . The equation can be expressed as follows:

$$y_t = W_{hy} h_t + b_y \tag{7}$$

where, W_{hy} is the weight matrix connecting the hidden state to the output layer. b_y is the bias term added to output. The output is generally fed into some activation function like sigmoid for a binary classification output or SoftMax for multiclass classifications.

3.5 Trained AE and RNN Model

The Autoencoder (AE) trained creates a model for compressing and reconstructing the input data thereby extracting useful features and reducing dimensionality [37]. Once trained, the latent features obtained through the encoder part of the Autoencoder serve as inputs to the RNN. The RNN model is then trained on these compressed features to identify the temporal patterns with the dependencies existing within the data for classification or prediction tasks. A loss function chosen is minimized using backpropagation and an optimizer such as Adam. The performance of the model on test data after training was assessed by measures such as accuracy or F1 score, and afterwards, the AE and RNN model is ready to be deployed to predict new data.

3.6 cloud deployment

The deployment of the models will involve hosting the trained Autoencoder (AE) and RNN model on the cloud platform for easy access and scalability for prediction making [38]. Such a model hosted in cloud services like AWS, Google Cloud, or Azure would thus be subjected to a large incoming volume of data. APIs are developed for possible integration with other applications for prediction tasks. This cloud infrastructure is flexible and scalable in case it needs to grow. The model would be continuously monitored to assess its performance and effectiveness. This model is also updated now and then through retraining with new data to maintain its accuracy.

4 RESULT AND DISCUSSION

The metrics concerned with the system resource utilization as appeared in the said periods are represented in the table. The columns capture CPU utilization, Memory usage, GPU utilization, Disk I/O, Network throughput, and Latency, pointing to different system performance metrics [39]. For instance, during the first point in time, CPU utilization was at 78%, memory usage at 74%, GPU utilization at 50%, Disk I/O at 68, network throughput at 34, and latency at 242 ms. It's very insightful in proving how each resource reacts to different states. For example, CPU utilization may reveal between 67% and 85%, whereas latency from 169 ms to 290 ms. These metrics serve critical importance in understanding the system's performance and bottleneck identification. The Ethnographic Health Systems Research (EHSR) approach, combining ethnographic methods with big data analytics to improve healthcare delivery, particularly in cardiology, is revealed by Srinivasan et al. (2023). Their method enhances decision-making, cost-effectiveness, and patient care. Using this approach, the proposed method integrates similar techniques to enhance early chronic kidney disease detection, improving outcomes and patient care [40].

Cpu utilization	Memory usage	Gpu utilization	Disk io	Network throughput	Latency
78	74	50	68	34	242
85	77	65	62	44	204
67	73	83	69	40	290
69	69	75	40	48	169
79	60	58	69	51	167
67	62	50	44	32	189

Figure 3: represents the training accuracy and validation accuracy across a total of 50 epochs in the training life cycle of the model. The training accuracy shows a steep rise indicated at the green line and attains a value of about one at around the 10th epoch indicating its rapid learning and fitting in the training data [41]. In contrast, validation accuracy shows slow increase sloping towards settle

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on a lower value than that of training accuracy, which is an indication that it might overfit. Overfitting happens when the model really tries to fit in the training data but has a poorer performance when faced with new uncharted data. It can be observed as depicted by the huge gap between training and validation accuracies after the 10th epoch. A hint toward needing to tune the model hence such as regularization or early stopping to improve generalization might be necessary.

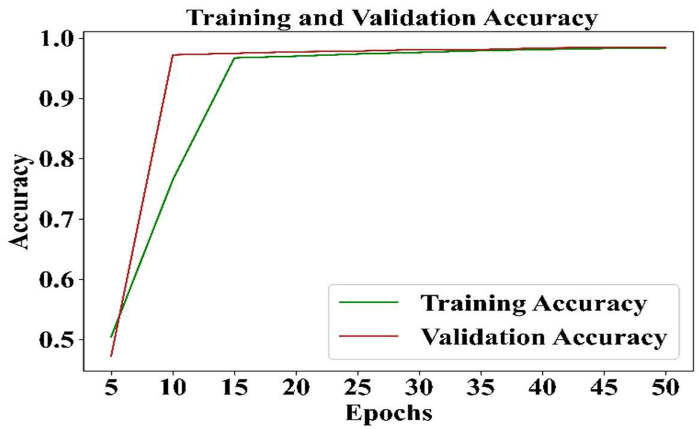

Figure 3: Training and validation accuracy

Figure 4: depicts the binary classifier's performance, identifying patients as having 'Disease' or 'Healthy.' The model achieved 362 True Positives (TP), where subjects were correctly predicted as "Disease" under the true label of the same name. This indicates that the model has been able to identify most cases of disease correctly. The False Positives (FP), where the model inaccurately predicted "Disease" for a true "Healthy" label, accumulated to 11, indicating that only a small value of cases was wrongly predicted as having disease. The False Negatives (FN), where the model indicated "Healthy" for a true "Disease" label, accounted for only 1, therefore suggesting that there are very few missed cases of disease. The True Negatives (TN) were 423, which was when the model correctly predicted "Healthy" and the true label was also "Healthy." This suggests good predictive power of healthy cases. Thus, overall, the computational model proved its worth by being strong in terms of true positive cases and low for misclassification. Dyavani et al. (2022) reveal a Transformer-based model for financial fraud detection, TransSecure, which uses self-supervised learning and Masked Transaction Modeling (MTM). It achieves 99.31% accuracy and 99.54% precision. Employing this approach, the proposed method adapts similar techniques to enhance early chronic kidney disease detection, improving diagnostic accuracy and minimizing false positives [42].

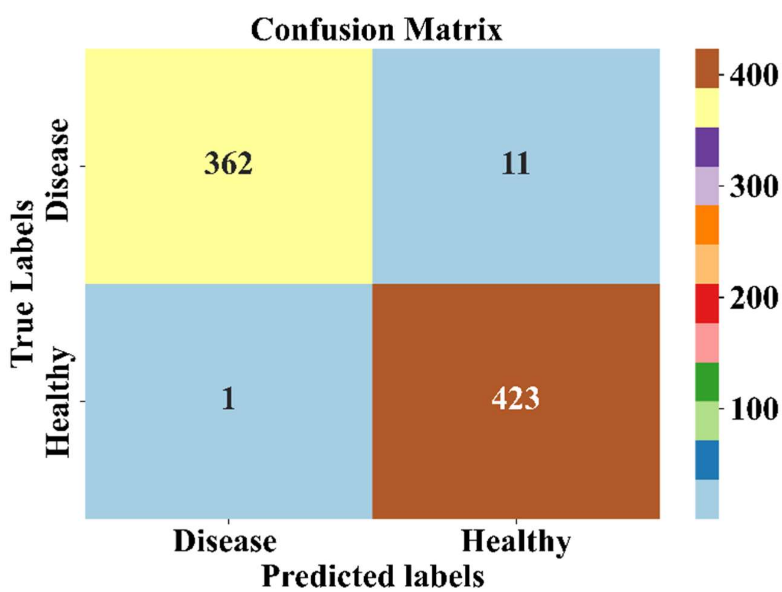

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Figure 4: Confusion Matrix

Figure 5: captures a number of evaluation metrics to measure the performance of a classification model. The best accuracy of model can be inferred from the value of 0.985; thus, it indicates that nearly all predictions made are right. The result of Precision is 0.975, which says that for most of the times, while predicting a positive result (disease), the model gives correct results. Sensitivity (to be known as Recall) stands on 0.998; that shows this model is good at pinpointing actual positives (disease). Specificity is 0.971 so it will be able to capture healthy people correctly pretty well. The F-measure score shows 0.986; therefore, the precision and recall have been balanced in that score. Finally, NPV (Negative Predictive Value) is 0.997, which indicates that prediction of very healthy individuals is recognized as well. Overall, the performance of the model is really impressive as per all the major parameters, with sensitivity and NPV being the top [43].

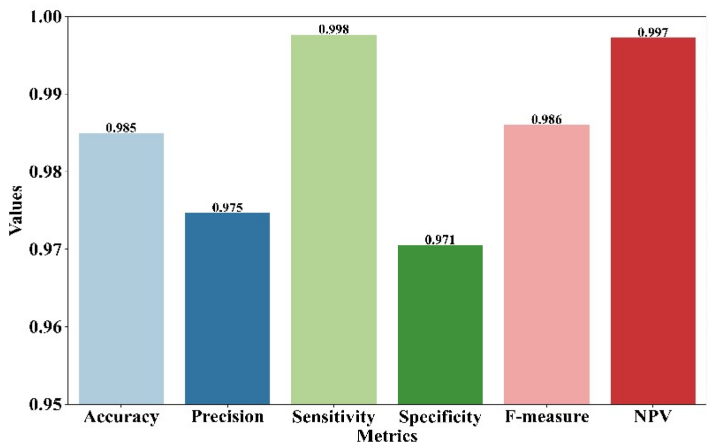

Figure 5: Performance metrics

Figure 6: shows the variation of various system metrics over a period of 24 hours. Each line corresponds to a single metric: CPU Utilization (blue), Memory Usage (green), GPU Utilization (orange), Disk I/O (red), Network Throughput (purple), and Latency (pink). The x-axis denotes hours in the time dimension and the metrics value on the y-axis. From the graph, it can be inferred that CPU Utilization and GPU Utilization show high spikes at certain hours corresponding to high activity, while Memory Utilization and Network Throughput tend to be stable through the day [44]. Disk I/O and Latency show lower fluctuation throughout. Such a pattern exhibits existence in system loads, which can be critical for performance monitoring and tuning. A robust AI-Augmented Test Automation Framework developed by Ramar et al. (2024) combines POM and BDD to enhance software testing efficiency, leveraging reinforcement learning for test case generation and self-healing to achieve 91% defect detection and 94% test coverage. Guided by these capabilities, the proposed method adapts similar AI techniques to improve early chronic kidney disease detection, enhancing scalability and efficiency [45].

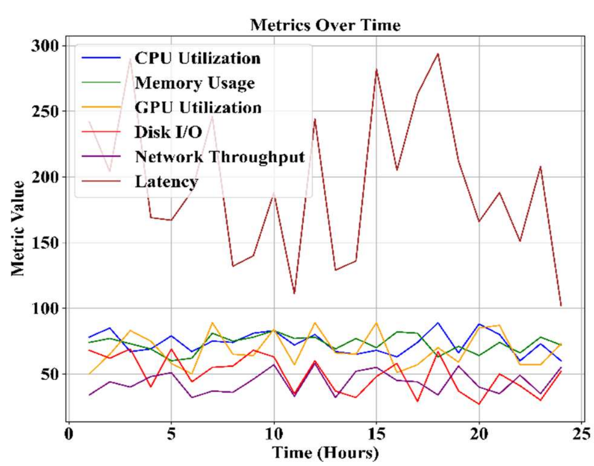

Figure 6: Metrics Over Time

5 CONCLUSION

This work proposes a sound architecture for detecting early CKD with an amalgamation of Autoencoders and Recurrent Neural Networks. The proposed method surpasses the old diagnostic methodologies by forging significant features extraction from Autoencoders and modelling time dependencies through RNNs. Further the effectiveness of the model was verified using various performance metrics such as accuracy, precision, and sensitivity with almost high values for all. This model can also be cloud deployed for scalability and enable continuous upgrading accessibility; hence it can be used realistically in healthcare applications. Further works could focus more on increasing the input diversity of the model and on enhancing its predictive quality.

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