Diagnosing Chronic Kidney Disease Through Deep Learning Approach

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***Abstract*—-chronic kidney disease (CKD) is a condition characterized by the gradual decline in kidney function, leading to the impaired ability to filter waste and fluids from the bloodstream. This buildup of toxins can result in various complications, including high blood pressure, anemia, cardiovascular issues, and ultimately, kidney failure. Early detection is crucial to mitigating these risks. In this research, we explore and compare two deep learning approaches—Artificial Neural Networks (ANN) and Sequential models—for predicting CKD using clinical patient data. By examining key health indicators such as red and white blood cell counts, we aim to assess the accuracy and performance of each model in classifying CKD. The findings will offer valuable insights into the effectiveness of deep learning techniques for disease diagnosis and prediction. Keywords- chronic kidney disease (CKD), Kidney Function Decline, Early Detection, Deep Learning, Artificial Neural Networks (ANN), Sequential Models, Clinical Patient Data, Health Indicators**

***Index Terms*—Keywords- chronic kidney disease (CKD), Kidney Function Decline, Early Detection, Deep Learning, Artificial Neural Networks (ANN), Sequential Models, Clinical Patient Data, Health Indicators.**

I. INTRODUCTION

Chronic Kidney Disease (CKD) is a progressive condition marked by the gradual decline of kidney function, impairing the body's ability to efficiently filter waste and fluids from the bloodstream. As toxins accumulate, patients face an increased risk of complications such as high blood pressure, anemia, cardiovascular disease, and eventually kidney failure. Early detection of CKD is vital for preventing these severe outcomes and improving patient care. In recent years, deep learning has emerged as a powerful tool for disease prediction and diagnosis.

This study focuses on leveraging deep learning techniques—specifically Artificial Neural Networks (ANN) and Sequential models—to predict CKD using clinical health data. By analyzing key health indicators like red and white blood cell counts, this research aims to compare the accuracy and performance of these two models. The goal is to determine which approach is more effective for the early detection of CKD, providing crucial insights into the role of deep learning in medical diagnostics.

II. OBJECTIVES

The purpose of this study is to develop and evaluate the performance of a Aritificial Neural Network (ANN) and a Sequential model for predicting chronic kidney disease (CKD) using patient health data. By comparing the accuracy of both models in identifying CKD, the study seeks to determine which approach is more effective. This comparison will provide valuable insights into the application of deep learning methods in the medical field, particularly for the early detection and diagnosis of chronic illnesses like CKD.

III. LITERATURE REVIEW

Fuzhe Ma, Tao Sun, Lingyun Liu, Hongyu Jing (2020) explains about the incidence of chronic kidney disease (CKD) continues to rise each year, highlighting the demand for more advanced therapeutic approaches. Machine learning techniques have become essential in predicting and diagnosing CKD, thanks to their ability to achieve high accuracy. An approach known as the Heterogeneous Modified Artificial Neural Network (HMANN), has been introduced for the early detection and diagnosis of chronic kidney failure, utilizing ultrasound imaging within the Internet of Medical Things (IoMT). This method offers substantial improvements in accuracy while also decreasing the time needed for contour delineation. **Farjana, A., Liza, F. T., Pandit, P. P., Das, M. C., Hasan, M., Tabassum, F., & Hossen, M. H. (2023)** this project explains how many individuals only pay attention to their health when symptoms arise, often due to demanding schedules. Chronic Kidney Disease (CKD) can be difficult to detect and prevent, as it frequently presents no early symptoms. Machine learning provides promising solutions for predicting and analysing such conditions. Nine different ML techniques were introduced, including KNN, SVM, Logistic Regression, Naïve Bayes, Extra Tree Classifiers, AdaBoost, XG Boost, and LightGBM. Among these, LightGBM demonstrated the highest accuracy in predicting CKD, achieving a 99% success rate.

Singh, V., Asari, V. K., & Rajasekaran, R. (2022) this paper tells how Chronic Kidney Disease (CKD) is often driven by conditions such as diabetes and high blood pressure, which progressively impair kidney function and heighten the risk of early mortality. Early detection of CKD remains difficult for healthcare providers. A newly developed deep learning model has shown remarkable performance in predicting and detecting CKD, achieving perfect accuracy. This model has successfully pinpointed critical features such as Haemoglobin, Specific Gravity, Serum Creatinine, and Hypertension using Recursive Feature Elimination (RFE). This advancement holds promise as a powerful tool for nephrologists, potentially enhancing the efficiency of CKD diagnosis. **Kriplani, H., Patel, B.& Roy, S. (2019)** in this paper they have, we utilized 224 records from the UCI Machine Learning Repository. Our deep neural network model achieved an impressive 97% accuracy in predicting the presence or absence of the disease. Early detection is vital for effective treatment and can significantly slow the progression of kidney damage.

Al Imran, A., Amin, M. N., & Johora, F. T. (2018) this paper tells that Chronic kidney disease (CKD) affects approximately 10% of adults globally and is among the top 20 leading causes of death. Although there is no cure, early diagnosis can help slow its progression. Given the shortage of nephrologists, modern machine learning techniques are crucial for effective CKD diagnosis. Our research evaluated logistic regression, feedforward neural networks, and wide & deep learning approaches for CKD diagnosis. The feedforward neural network demonstrated the highest performance, with a 0.99 F1-score, 0.97 precision, 0.99 recall, and 0.99 AUC score. Logistic regression yielded the lowest results, while wide & deep learning proved effective with larger datasets due to its multiple hidden layers and neurons. **Akter, S., Habib, A., Islam, M. A., Hossen, M. S., Fahim, W. A., Sarkar, P. R., & Ahmed, M. (2021)** this paper depicts global incidence of chronic kidney disease (CKD) is on the rise. Although asymptomatic CKD is prevalent, guideline-based monitoring for its prediction is often underused. Computer-aided diagnostic (CAD) systems, particularly those using deep learning algorithms, offer accurate prediction and classification of CKD based on various clinical features. In a study employing seven deep learning algorithms, models such as Artificial Neural Networks (ANN), Simple Recurrent Neural Networks (RNN), and Multi-Layer Perceptrons (MLP) achieved high accuracy rates of 99%, 96%, and 97%, respectively. These advanced models not only demonstrated improved prediction capabilities but also reduced computation times compared to traditional methods. Their superior performance suggests they could significantly enhance CKD prediction within the Internet of Medical Things (IoMT) framework, contributing to more efficient and effective healthcare analytics.

Mondol, C., Shamrat, F. J. M., Hasan, M. R., Alam, S., Ghosh, P., Tasnim, Z., ... & Ibrahim, S. M. (2022) this paper refers that Chronic Kidney Disease (CKD) is a significant health issue, and timely diagnosis and management are vital for improving patient outcomes. A recent study evaluated advanced neural network models against traditional ones for CKD diagnosis based on 24 attributes. The research found that optimized models—such as Optimized Convolutional Neural Networks (OCNN), Optimized Artificial Neural Networks (OANN), and Optimized Long Short-Term Memory (OLSTM)—outperformed their traditional counterparts. Among these, OCNN achieved the highest accuracy at 98.75%, an AUC score of 0.99, and the fastest compilation time of 0.00447 seconds, establishing it as the most effective model for CKD classification. **Shankar, K., Manickam, P., Devika, G., & Ilayaraja, M. (2018)** this paper explains that Chronic Kidney Disease (CKD) is a condition characterized by a gradual loss of kidney function, which can be challenging to diagnose early. A novel approach involves using an optimization model combined with advanced learning techniques to analyse CKD stages from office visit records, facilitating earlier detection and intervention. This method utilizes Ant Lion Optimization (ALO) to identify the most relevant kidney data features for classification with a Deep Neural Network (DNN). The use of ALO enhances the accuracy and performance of CKD classification compared to other classification methods.

Chittora, P., Chaurasia, S., Chakrabarti, P., Kumawat, G., Chakrabarti, T., Leonowicz, Z., ... & Bolshev, V. (2021) this paper refers to Chronic Kidney Disease (CKD) as a common condition where early diagnosis is crucial for effective management. Machine learning algorithms are increasingly important for detecting CKD in a timely manner. A study using the CKD dataset from the UCI repository evaluated seven different classifier algorithms. Among these, LSVM with L2 penalty achieved the highest accuracy of 98.86% when combined with synthetic minority over-sampling technique and full feature set. Other performance metrics such as precision, recall, and F-measure were also assessed. Additionally, a deep neural network model demonstrated a remarkable accuracy of 99.6%. This study underscores the role of machine learning in CKD prediction and highlights the effectiveness of various algorithms and feature selection methods. **Tekale, S., Shingavi, P., Wandhekar, S., & Chatorikar, A. (2018)** in this paper it refers to the fast-paced modern world, individuals often overlook their health until symptoms become noticeable. Chronic Kidney Disease (CKD) can be particularly challenging to detect early, as it might not present clear symptoms. Machine learning provides a promising solution for precise prediction and analysis using data from 400 CKD patients with 14 different attributes. Methods such as Decision Tree and Support Vector Machine (SVM) are employed to predict the presence and severity of CKD with high accuracy, offering valuable tools for early diagnosis and intervention.

Debal, D. A., & Sitote, T. M. (2022) this paper explains that the Goal three of the UN's Sustainable Development Goals is to promote good health and well-being, with a focus on reducing premature mortality from non-communicable diseases by a third by 2030. Chronic kidney disease (CKD) is a significant contributor to global morbidity and mortality, affecting 10-15% of the population. Early detection of CKD stages is crucial to minimize health complications. Machine learning techniques, such as Random Forest, Support Vector Machine, and Decision Tree, have been used to predict CKD stages. Results show that Random Forest with recursive feature elimination and cross-validation outperforms SVM and DT in predicting CKD stages. **Iliyas, I. I., Saidu, I. R., Dauda, A.**

B., & Tasiu, S. (2020) this article explains that Deep neural networks (DNNs) play a crucial role in machine learning, offering valuable applications in areas such as health image processing for detecting diseases like cancer and diabetes. Kidney disease represents a major health concern, and failing to address its symptoms can lead to chronic kidney disease and serious health complications. In Yobe State, Nigeria, CKD is widespread, yet there is a gap in effective technological solutions. A DNN model developed using data from Bade General Hospital demonstrated a high accuracy of 98% in detecting CKD in patients. The analysis highlighted creatinine and bicarbonate as key features for diagnosing CKD.

Radha, N., & Ramya, S. (2016) this article explains that Chronic Kidney Disease (CKD) involves a gradual reduction in kidney function, often resulting from diabetes and high blood pressure. This study focuses on employing classification algorithms to swiftly and accurately diagnose kidney function failure using data from medical reports. The findings indicate that the Radial Basis Function (RBF) algorithm excels compared to other methods, achieving an accuracy of 85.3% in identifying the severity stages of CKD. **Qin, J., Chen, L., Liu, Y., Liu, C., Feng, C., & Chen, B. (2019)** explains that chronic kidney disease (CKD) is a significant global health issue, characterized by high morbidity and mortality rates and often leading to additional health complications. Early detection of CKD is critical, as it can be asymptomatic in its initial stages. Machine learning models provide a means for rapid and precise diagnosis, supporting clinicians in their evaluations. In this study, we applied a machine learning approach using a CKD dataset from the UCI repository. Missing values were addressed using KNN imputation, and six different algorithms were evaluated. The Random Forest algorithm achieved the highest accuracy at 99.75%. Additionally, combining logistic regression and Random Forest models through a perceptron yielded an average accuracy of 99.83% across multiple simulations. This approach demonstrates significant potential for improving the diagnosis of complex clinical data.

B**aidya, D., Umaima, U., Islam, M. N., Shamrat, F. J. M., Pramanik, A., & Rahman, M. S. (2022)**, explains that chronic kidney disease (CKD) has emerged as a significant global health issue, making early diagnosis essential to prevent its advancement. Recent advancements in machine learning have enabled doctors to identify CKD at earlier stages. This study employed eight different machine learning algorithms to detect CKD using patient health data from a hospital-provided dataset. The results revealed that K-Nearest Neighbours and Extra Tree Classifier achieved the highest accuracy of 99%, outperforming Gradient Boost, which achieved 98%. The evaluation of these algorithms included metrics such as F1-score, precision, accuracy, recall, and AUC score to assess their performance comprehensively.

IV. METHODOLOGY

A. *Data Collection*

The dataset used in this study was sourced from Kaggle and comprises 26 columns and 280 rows, representing various patient attributes such as age, as well as clinical measurements like blood pressure (bp) and specific gravity (sg) of urine, the latter of which helps assess urine concentration. Levels of albumin (al) and sugar (su) in urine provide insights into kidney function and potential diabetes risk, respectively. Red blood cell count (rbc) and pus cell count (pc) are indicators of potential kidney damage or infections, with the presence of pus cell clumps (pcc) and bacteria (ba) suggesting possible urinary tract infections. Further attributes include blood glucose random (bgr), which provides a snapshot of blood sugar levels, blood urea (bu), and serum creatinine (sc), both markers of kidney health and function. Electrolyte balance is represented by sodium (sod) and potassium (pot) levels, which are vital for proper heart and kidney function. Haemoglobin (hemo) and packed cell volume (pcv) are also recorded, offering insights into oxygen-carrying capacity and anaemia status, respectively, while white blood cell (wc) and red blood cell (rc) counts offer additional details on immune response and potential kidney impairment. Hypertension (htn) status and the presence of diabetes mellitus (dm) provide key risk factors, along with coronary artery disease (cad), all of which can affect kidney health. Lifestyle-related indicators, including appetite (appet), recorded as either good or poor, and pedal edema (pe), a sign of swelling in the feet and ankles, further enrich the data by reflecting potential symptoms associated with kidney issues. Additionally, anemia (ane) status is included as an important factor in kidney disease diagnosis. The target variable, classification, signifies the presence or absence of kidney disease, making this dataset well-suited for training models to predict disease status based on these diverse health markers. The dataset contains null values, which will be addressed through data preprocessing.

B. *Data Preprocessing*

Preprocessing is essential to handle missing values, normalize the data, and prepare it for model training and evaluation. The steps involved in preprocessing include: **Handling Missing Values:** Missing values are identified and handled by using appropriate imputation techniques. Numerical columns may use mean or median imputation, while categorical columns may use the mode. **Feature Scaling:** To ensure that all feature values are on a similar scale, Min-Max scaling or Standardization is applied. This process helps improve the stability and performance of the models. **Feature Selection:** Although all 26 columns are included initially, feature selection may be performed if further analysis reveals that specific attributes contribute more to model accuracy or if the model's complexity must be reduced for improved generalization.

C. *Model Selection*

This study utilizes two distinct models: an Artificial Neural Network (ANN) model with custom layer configurations and a Sequential model with slightly different settings. The ANN and Sequential models are implemented to assess the average loss and average accuracy metrics.

ANN Model:

- **Architecture:**The ANN model is designed with three dense layers and an input layer size matching the number of features.
- **Activation:** Leaky ReLU is used for hidden layers to handle gradient issues.
- **Dropout:** A dropout layer with a 30% rate is applied after each hidden layer to mitigate overfitting.
- **Optimizer:** Adam optimizer is employed with a learning rate to balance convergence speed and performance.

Sequential Model:

- **Architecture:**The Sequential model mirrors the ANN architecture, with minor variations in activation functions (using ReLU).
- **Optimizer and Loss:** Similar to the ANN model, Adam and MSE are used for optimization and loss calculation.

D. Model Training and Cross-Validation

To evaluate the models effectively, 5-fold cross-validation is employed, allowing each model to be trained and validated on different data splits and thus improving generalization.

Cross-Validation Setup: K-Fold cross-validation with 5 splits is performed. For each fold, 80% of the data is used for training, and 20% is retained for validation.

Training Procedure: Each model is trained for 500 epochs with a batch size of 32. Early stopping may be applied if necessary to prevent overfitting. **Metrics:** Each fold's results are recorded for loss and accuracy

E. Model Evaluation Metrics

Accuracy: Accuracy is a percentage measure, often ranging between 0 and 100%, showing how well the model performed based on the fraction of correct predictions out of the total predictions.

Loss: reflects the error in terms of the difference between the predicted probabilities and the actual target distribution. While lower loss generally correlates with higher accuracy, they are not always directly proportional, especially in the early stages of training when the model is still learning.

F. Results and Analysis

Results from each model are averaged across all five folds for comparison:

Performance Comparison: The average loss and average accuracy of the ANN and Sequential model's are calculated to assess consistency and accuracy.

Observations: The model with high average accuracy is deemed to perform better.

V. ARCHITECTURE OF ANN AND SEQUENTIAL MODEL

Artificial Neural Network (ANN): The ANN model starts with an input layer that has 128 neurons, corresponding to the number of input features from the dataset after scaling. The choice of 128 neurons allows the model to process and extract significant features from the input data. The first hidden layer uses the Leaky ReLU activation function, which introduces non-linearity, allowing the model to learn from the data more effectively than traditional activation functions like ReLU. Leaky ReLU also helps mitigate issues like the vanishing gradient problem, where gradients can become too small to make significant updates during backpropagation.

To further improve the model's generalization, a Dropout layer is added after the first hidden layer with a dropout rate of 0.3, meaning that 30% of the neurons are randomly deactivated during each training epoch. This technique helps prevent overfitting by ensuring the model does not rely too heavily on any specific feature or neuron. Following the dropout layer, a second hidden layer with 64 neurons is added, again using the Leaky ReLU activation function to introduce more complexity into the learned patterns. The Leaky ReLU activation function is used in the model architecture to address some of the limitations of the standard ReLU (Rectified Linear Unit) function and improve the performance of the neural network, particularly in cases where the model might encounter issues like the vanishing gradient problem or slow learning.

Sequential Model Architecture: The Sequential model shares a similar structure to the ANN but with one key difference—the first hidden layer uses the ReLU activation function instead of Leaky ReLU. ReLU is commonly used in neural networks due to its simplicity and effectiveness in enabling the model to learn complex patterns, but it can suffer from the vanishing gradient problem with certain types of data. In this case, the choice to use standard ReLU was to explore whether a simpler approach would yield similar performance.

Like the ANN, the Sequential model also includes a Dropout layer with a dropout rate of 0.3 and a second hidden layer with 64 neurons, both using the ReLU activation function. The final layer is also a single neuron, outputting the continuous predicted value, with no activation function applied. This model is compiled in the same way as the ANN, using the Adam optimizer with a learning rate of 0.0005 and the loss function and accuracy to evaluate the model's predictive capability.

VI. ANALYSIS OF RESULT

The results of both the ANN model and the Sequential model suggest that both models have performed well in predicting the target variable, with the Sequential model showing a slightly better overall performance in terms of lower loss and higher accuracy.

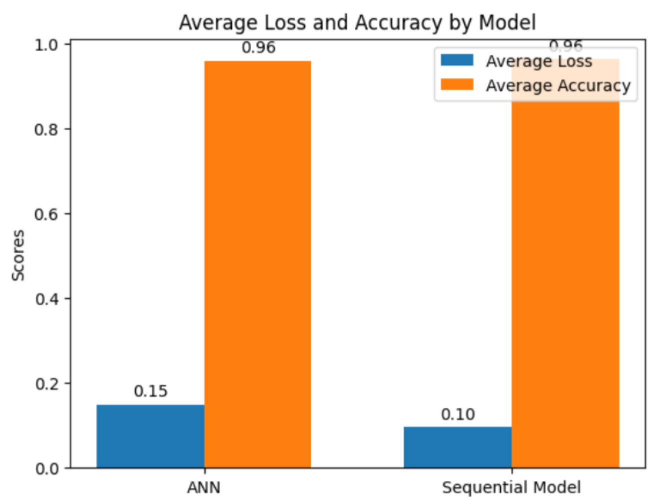
ANN Model:
The ANN model achieved an average loss of **0.1493**, indicating that the model's predictions are fairly close to the actual values but could be improved. This loss level suggests that the model has successfully learned the underlying patterns in the data to a reasonable extent, but there is some room for further optimization.

The average accuracy of 95.99% demonstrates that the ANN model correctly predicts the target variable in almost

96% of cases, which is a strong performance. This high accuracy level confirms that the ANN model can reliably capture relationships within the dataset, making it a competent predictor of the target variable.

Sequential Model:
The Sequential model shows a lower average loss of **0.0966**, which is a marked improvement over the ANN model's loss. This lower loss value indicates a better fit to the data and suggests that the Sequential model's architecture is able to make more precise predictions with fewer errors.

With an average accuracy of 96.43%, the Sequential model slightly outperforms the ANN model. This improvement in accuracy, though small, indicates that the Sequential model has a slightly superior ability to capture and generalize the relationships in the dataset, leading to a more accurate representation of the target variable.



VII. CONCLUSION

In this study, two deep learning models—the Artificial Neural Network (ANN) and the Sequential model—were employed to predict outcomes based on a Kaggle dataset comprising 26 attributes related to various patient health metrics. The performance of both models was evaluated through K-fold cross-validation, where key metrics such as Average Loss and Average Accuracy were used to assess predictive performance.

The results indicate that the Sequential model outperforms the ANN model across both evaluation metrics. Specifically, the Average Loss for the Sequential model is lower than that of the ANN model, suggesting that the Sequential model makes fewer prediction errors overall. Similarly, the Average Accuracy for the Sequential model is slightly higher, indicating that it correctly predicts the target variable in a greater proportion of cases compared to the ANN model. This improved accuracy demonstrates that the Sequential model captures more of the underlying patterns in the data, providing a more accurate representation of the relationship between the input features and the target variable.

While both models are effective in making predictions on this dataset, the Sequential model's architecture, which employs multiple layers of dense neurons and activation functions, appears to offer a more robust and accurate mapping of the data. The use of ReLU and Leaky ReLU activation functions, in conjunction with Dropout layers, has likely contributed to the model's ability to avoid overfitting while maintaining strong predictive power.

Despite the Sequential model's superior performance, it is essential to acknowledge the presence of unexplained variance, as reflected in the residual error and the Average Loss value being above zero. This suggests that there are still factors influencing the target variable that the model has not fully captured. Further refinement of the models, through exploring alternative architectures, could help in reducing prediction errors and achieving even greater accuracy in future iterations.

VIII. FUTURE WORK

Future iterations could explore more sophisticated architectures, such as deeper or more complex neural networks (e.g., Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs)) or models combining both deep learning and classical machine learning techniques.

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