

# Hybrid Model Combining Deep Neural Network and XGBOOST for Predicting Chronic Kidney Disease

Kasimu Abba Musa<sup>1</sup> and Asabe Sandra Ahmadu<sup>2</sup>

<sup>1</sup> Department of Computer Science, Modibbo Adama University, Yola, Adamawa, Nigeria

<sup>2</sup> Department of Computer Science, Modibbo Adama University, Yola, Adamawa, Nigeria  
alkasim232@gmail.com<sup>1</sup>, ahmaduasabe@mau.edu.ng<sup>2</sup>

## Abstract

**Background:** chronic kidney disease is a global public health issues that affect approximately one billion people globally. kidney disease affect people in different ways across the world. **Aim** of this study is to enhance the prediction performance of chronic kidney disease (CKD) by developing a hybrid model that combing deep neural network and XGBoost algorithms, by utilizing a comprehensive set of features derived from clinical data, the model was designed to distinguish between healthy individuals and those at risk of CKD. The approach involved analyzing various metrics such as accuracy, precision, recall, and F1-score to evaluate model performance comprehensively. **Model** achieved an accuracy of 92%, with precision at 94% and recall at 92%, indicating its robustness in identifying positive cases while minimizing false positives. Data were collected from patient records, and a hybrid model was implemented, combining different algorithms to enhance predictive capabilities. The training process utilized multiple iterations to optimize the model's performance, resulting in a well-generalized tool for clinical practice. These findings suggest that the implementation of such a predictive model can significantly improve early detection and management of chronic kidney disease, thereby enhancing patient outcomes and resource allocation in healthcare settings. Future research should explore additional features and methodologies to further refine prediction accuracy and applicability in diverse clinical environments.

## 1. Introduction

Chronic kidney disease (CKD) is a significant global public health issue, affecting nearly 1 billion people worldwide, with a notable prevalence in the United States where over 37 million individuals are affected, and many remain unaware of their condition (Okpechi *et al.*, 2024) (Francis *et al.*, 2024). The burden of CKD is particularly pronounced among older adults, with prevalence rates reaching 38% in those over 65 years (Francis *et al.*, 2024). Economically, CKD imposes substantial costs on healthcare systems, exacerbated by its rising incidence, which has made it the 12th leading cause of death globally, increasing from 17th place in 1990 (Jadoul *et al.*, 2024) (Bello *et al.*, 2024). In the Middle East, CKD prevalence ranges from 5.2% to 10.6%, with treated kidney failure rates varying significantly across countries, highlighting disparities in healthcare access and management (Bello *et al.*, 2024). This multifaceted challenge necessitates urgent public health interventions to improve awareness and treatment accessibility (Francis *et al.*, 2024) (Jadoul *et al.*, 2024). Chronic kidney disease (CKD) prevalence in Nigeria varies significantly across studies, with estimates ranging from 2.5% to 26.6%. A study by (Lang *et al.*, 2022). Reported an age- adjusted prevalence of 13% in Kwara State, based on a sample of 1,353 individuals screened for CKD (Lang *et al.*,

2022). Common risk factors identified included old age, obesity, diabetes mellitus, hypertension, and family history of renal disease (Odonmeta *et al.*, 2024). Additionally, Dada *et al.* (2019) noted that patients with a family history of CKD had a significantly lower hazard ratio for survival on dialysis, emphasizing the importance of familial risk factors in CKD outcomes (Odonmeta *et al.*, 2024). Chronic kidney disease (CKD) is a progressive condition characterized by the gradual loss of kidney function over time, leading to an inability to effectively filter waste products from the blood, which can result in severe health complications and increased mortality risk (Huang *et al.*, 2023) (Brandenburg & Saritas, 2023). The prevalence of CKD is rising globally, driven by factors such as an aging population, obesity, diabetes, and hypertension (Huang *et al.*, 2023). CKD is often linked with acute kidney injury (AKI), where episodes of kidney damage can exacerbate the progression to CKD (Chou, 2023). The path physiology of CKD is complex, involving mechanisms such as kidney fibrosis, which is primarily driven by resident fibroblasts (Huang *et al.*, 2023). Furthermore, CKD has been associated with cognitive decline and conditions like Alzheimer's disease, particularly through the activation of the rennin - angiotensin system (Ma *et al.*, 2023). Early detection and management strategies, including the use of machine learning for risk assessment, are crucial for improving outcomes in CKD patients (Pal, 2023). Chronic kidney disease (CKD) often progresses silently in its early stages, with non-specific symptoms such as fatigue, dizziness, and loss of taste that are frequently overlooked by patients and healthcare providers alike (Mamatha & Terdal, 2024) (Ramer & Koncicki, 2023). This lack of early detection can lead to severe complications, including glomerular malfunction and kidney infections, ultimately resulting in end-stage renal failure (Meena *et al.*, 2023) (Al-Hakeim *et al.*, 2023). The symptom burden in advanced CKD is significant, with patients experiencing a range of issues that can severely impact their quality of life, including chronic fatigue and affective symptoms (Palencia, 2022) (Al-Hakeim *et al.*, 2023). Moreover, CKD is associated with increased risks of cardiovascular diseases, hypertension, and bone disorders, highlighting the interconnectedness of kidney health with overall bodily functions (Meena *et al.*, 2023). Early diagnosis and proactive management are crucial to prevent the progression of CKD and its associated complications, emphasizing the need for heightened awareness and better healthcare delivery systems (Mamatha & Terdal, 2024) (Meena *et al.*, 2023). Early detection of chronic kidney disease (CKD) is crucial for effective management and can significantly reduce morbidity and mortality associated with the condition. However, a staggering 96% of individuals with kidney dysfunction remain unaware of their CKD status, primarily due to the asymptomatic nature of early stages and insufficient diagnostic practices (Levin *et al.*, 2023). Leveraging existing diagnostic databases can enhance early detection efforts, as these centres already collect extensive data that can be utilized to identify CKD through routine blood and urine tests (George *et al.*, 2022) (Pecoits-Filho *et al.*, 2023). For instance, integrating kidney function markers into current screening programs for other non-communicable diseases, such as diabetes and hypertension, can facilitate the identification of at-risk individuals (George *et al.*, 2022). Moreover, guidelines recommend regular screening for CKD in patients with type 2 diabetes, emphasizing the need for systematic approaches to improve awareness and diagnosis (Skolnik & Style, 2021). By prioritizing early detection, we can prevent the progression of CKD and improve patient outcomes (Friedman, 2022).

## 2. Related Work

Chronic kidney disease (CKD) is increasingly prevalent due to factors such as excessive alcohol consumption, environmental pollution, and lifestyle choices, leading to late-stage diagnoses and significant mortality rates (Kumar & Singla, 2024; Thakkar *et al.*, 2024). Early prediction of kidney illness using classification and regression algorithms is an effective endeavour that can assist doctors in quickly diagnosing the condition. Several studies have explored machine learning-based approaches to improve CKD detection. Ghosh *et al.* (2024) conducted a comparative analysis of machine learning algorithms and proposed a hybrid model that enhances prediction accuracy for CKD diagnosis. Similarly, Uddin *et al.* (2024) evaluated multiple prediction models and emphasized the importance of model selection for early detection, highlighting the superior performance of ensemble-based approaches. Furthermore, Rahman, Al-Amin, and Hossain (2024) investigated various machine learning techniques for CKD diagnosis, demonstrating that deep learning models can achieve high predictive accuracy in medical applications. Despite these advancements, doctors continue to face a difficult burden in detecting renal illness at an early stage.

There are very less means to identify them at an early stage. In order to get required knowledge about various concepts related to the present application, existing literature were studied. Some of the important conclusions such as our problem statements (research gap) were made through some of the literatures listed below. (Poonia *et al.*, 2022), provides an excellent feature-based prediction model for detecting kidney disease. Various machine learning algorithms, including k-nearest neighbor's algorithm (KNN) and support vector machines (SVM) were used to build and analyze various prediction models on a publicly available dataset of healthy and kidney disease patients.

A logistic regression-based prediction model with optimal features chosen using the Chi-Square technique had the highest accuracy of 98.75%. However, Rady and Anwar (2019), suggests that the severity stages of chronic kidney disease can be accurately classified and predicted by using data mining techniques. The Probabilistic Neural Networks and Radial Basis Function techniques are providing the most accurate classification, precision, and highest F-Measure, comparable to the Support Vector Machine and Multilayer Perception techniques. A studies show that MLAs can provide timely predictions of death by disease (DKD) among patients with recently diagnosed T2DM. Two MLAs were trained to predict stages of DKD severity, and compared with the Centers for Disease Control and Prevention's risk score (Allen *et al.*, 2022).

In another study by (Segal *et al.*, 2020), introduced an ensemble tree-based machine learning algorithm (XGBoost) for the early identification of renal disease. A comparison was made between the provided model and Random Forest, Cat Boost, and Regression with Regularization. All matrices demonstrated improved performance for the proposed model, including c-statistics of 0.93, sensitivity of 0.715, and specificity of 0.958. (Khamparia *et al.*, 2020) created a deep learning model utilizing stacked auto encoders to extract features from multimedia data for the early identification of CKD. To forecast the final class, the authors utilized a Soft Max classifier. On the UCI CKD data set, it was found that the suggested model performed the best when compared to traditional classification strategies.

Chimwayi *et al.* (2017) has given a statement about the risk level prediction of CKD using Neuro-Fuzzy classifier. They also used Hierarchical Clustering and found three forms of clusters and a strong relationship between CKD and diabetes. Another one by (Gharibdousti *et al.*, 2017), they applied Decision Tree, Linear Regression, Super Vector Machine, Naïve Bayesian and Neural Network model to predict kidney disease. The data set was also collected from UCI repository. Mahalakshmi *et al.* (2019) used some classification techniques such as CNN, MLP, RBFN to predict kidney disease in diabetic patients. Their main work was to find the best classification technique based on excellent accuracy.

Are search paper on the detection of chronic kidney disease (CKD) using machine learning algorithms while taking to account the smallest subset of features was developed, according to (Almasoud & Ward, 2019). The performances of four classifiers, logistic regression, support vector machines (SVM), random forest, and gradient boosting were assessed, and redundant features were removed using statistical tests. The findings demonstrate that the gradient boosting algorithm, which in corporate three crucial features which includes, hemoglobin, albumin, and specific gravity, achieves the highest accuracy (99.1% by the F1- measure). The study recognizes that three of these characteristics are enough to determine CKD with accuracy and recommends further research with larger sample populations to search for and confirm the occurrence of CKD probability in at-risk patients.

The paper "Chronic Kidney Disease Prediction Using Machine Learning Models" by Revathy, Bharathi, Jeyanthi, and Ramesh (2019) presents the development of a prediction model for early detection of chronic kidney disease (CKD). The results indicated that the Random Forest Classifier was more precise in CKD prediction compared to Decision Trees and support vector machine.

As an additional means of improving predictive accuracy, the authors suggested comparison based on execution time as well as feature set selection. Another study by Xiao *et al.* (2019) used statistical analysis, machine learning algorithms, and neural network models to construct and compare prediction models for chronic kidney disease (CKD) progression. Nine models were examined, and the linear models with the highest predictive power were logistic regression, lasso regression, elastic net regression, and ridge regression. The predict ability of the models was found to be significantly impacted by blood markers (ALB, Scr, TG, LDL, and EGFR). As potential areas for further development, the authors advise comparing the models according to execution speed and feature set preference.

Gudeti *et al.* (2020) suggested a novel approach of Chronic Kidney Disease (CKD) prediction using Machine Learning Algorithms. According to the discussion provided by the authors, the Support Vector Machine (SVM) algorithm performed better than Logistic Regression and K-Nearest Neighbors (KNN) as far as the precision metric was concerned for predicting chronic kidney disease. This approach not only makes predictions at a faster speed but also enables early initiation of treatment for CKD patients, which can benefit more individuals. An independent research study by Yashfi *et al.* (2020) proposes a framework that uses machine learning algorithms to calculate the risk of chronic kidney disease (CKD) based on a patient dataset of 455. The study finds that the

Random Forest algorithm works at a 97.12% accuracy, while the Artificial Neural Network algorithm works at 94.5% accuracy.

Ekanayake and Herath (2020) provide a methodological approach that combines data preprocessing, missing value treatment, and feature selection for predicting Chronic Kidney Disease (CKD) status from clinical data. Both the random forest classifier and the extra tree classifier were found to be more accurate with reduced bias. This paper highlights the pragmatic aspects of data collection as well as the importance of domain knowledge in the use of machine learning methods in CKD prediction.

The paper "Predicting the Risk of Chronic Kidney Disease (CKD) Using Machine Learning Algorithm" by Wang, Chakraborty, and Chakraborty (2020) suggests a risk prediction model for CKD using easily accessible health features. The authors use under sampling methods along with a novel cost-sensitive mean-squared error (MSE) loss function to compare three machine learning models. Of these, the ensemble model performed best with an R2 score of 0.5590. The authors claim that their system can predict the risk of Chronic Kidney Disease (CKD) from commonly available health metrics, enabling the selection of high-risk patients who can be advised to take a creatinine test for confirmation. Chen *et al.* (2020), in a study, introduce an Adaptive Hybridized Deep Convolutional Neural Network (AHDCNN) for active CKD prediction and diagnosis. The model AHDCNN applies advanced deep learning algorithms and methods for classification to effectively detect different kidney cancer subtypes and facilitate early detection and appropriate therapy to avoid the development of the disease to its terminal stage. The technique integrates region of interest annotations with deep learning methods by radiologists to show promising outcomes in the classification of renal cell subtypes.

Alloghani *et al.* (2020) the author focuses on the use of machine learning algorithms for the prediction of CKD in cardiovascular disease patients with high risk based on their historical medical information. 12 supervised machine learning algorithms were used to classify 544 outpatients into two groups: advanced CKD and early-stage CKD. Polynomial Support Vector Machine algorithm proved to be the most effective and efficient, with a rate of 93.4% efficiency and 91.7% classification accuracy. Future research should incorporate creatinized Glomerular Filtration Rate to ensure that the classification integrates the five stages of CKD. Sobrinho *et al.* (2020) conducted a comparative analysis of machine learning techniques to assist in the early detection of chronic kidney disease (CKD) in developing countries. Findings indicated that the J48 decision tree was most appropriate to assist in the diagnosis of CKD in resource-limited environments, reducing the disease burden in developing nations, with 95.00% accuracy and strong agreement with an experienced nephrologist's view. Other methods like random forest, naive Bayes, support vector machine, multilayer perceptron, and k-nearest neighbor were less accurate but also had moderate agreement with the nephrologists.

Another study by Sabanayagam *et al.* (2020) they developed a DLA to detect chronic kidney disease from retinal images, with a higher prevalence of diabetes and hypertension in the SEED dataset. The features of the subjects of the training and validation data sets were comparable, with more diabetes in the validation data set. The majority of the cases in all data sets were stage 3 CKD, with some

advancing to stage 5. The paper concludes that the DLA of retinal images can detect CKD in community populations Chittora *et al.* (2021) proposed a machine learning-based study for predicting Chronic Kidney Disease (CKD). Seven models of classification, i.e., artificial neural network, C5.0, Chi-square Automatic interaction detector, logistic regression, linear support vector machine (LSVM) with penalties L1 and L2, and random tree, were used on CKD data in the UCI repository.

Despite the promising results achieved by machine learning algorithms in predicting chronic kidney disease (CKD), several research gaps remain. While LSVM with L2 penalty demonstrated high accuracy (98.86%) in SMOTE with full features, and Random Forest achieved 99.75% accuracy in previous studies, there is still a need to explore more robust and generalizable models. Feature selection methods, including correlation-based selection, wrapper approaches, and LASSO regression, have been effective, but optimizing feature engineering techniques could further enhance model performance. Additionally, while hyperparameter tuning has shown significant improvements, the integration of deep learning and neural networks remains underexplored. Future studies should focus on leveraging advanced deep learning architectures, hybrid models, and ensemble learning to improve CKD diagnosis accuracy and generalizability. Moreover, expanding predictive modeling to other related illnesses and incorporating real-time clinical data could lead to more reliable and early detection frameworks, ultimately improving patient outcomes.

### 3. Methodology

This section outlined the different materials and the methodology employed in developing the model.

#### 3.1 Data Source

The chronic kidney disease (CKD) dataset used in this study is a secondary dataset that was obtained from the University of California Irvine (UCI) machine learning repository. The CKD dataset includes 400 samples, 24 features, and 1 class label. The class label has two values: CKD (sample with CKD) and not CKD (sample without CKD).

#### 3.2 Feature Extraction and Handling Missing Data

Feature selection is a process used in machine learning to identify the most important or relevant features (variables, columns) in a dataset that contribute the most to the prediction or classification task. It helps in improving the model's performance by reducing overfitting, speeding up the training process, and making the model easier to interpret by eliminating irrelevant or redundant features. In this research we used two methods which are Extra Tree Classifier and Deep Neural Network (DNN).

#### 3.3 Performance Evaluation Metrics

The models were evaluated using four standard metrics: accuracy, precision, recall, and F1 score, where TP stands for true positive, TN stands for true negative, FP stands for false positive, and FN stands for false negative.

### a. Accuracy

It is the number of correct predictions made by the model divided by the total number of predictions made by the model

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (3.1)$$

### b. Precision

The precision is referred to the number of positive divided by the total number of actual positive.

$$Precision = \frac{TP}{TP+FP} \quad (3.2)$$

### c. Recall

It is the number of true positives divided by the total number of actual negative.

$$Recall = \frac{TP}{TP+FN} \quad (3.3)$$

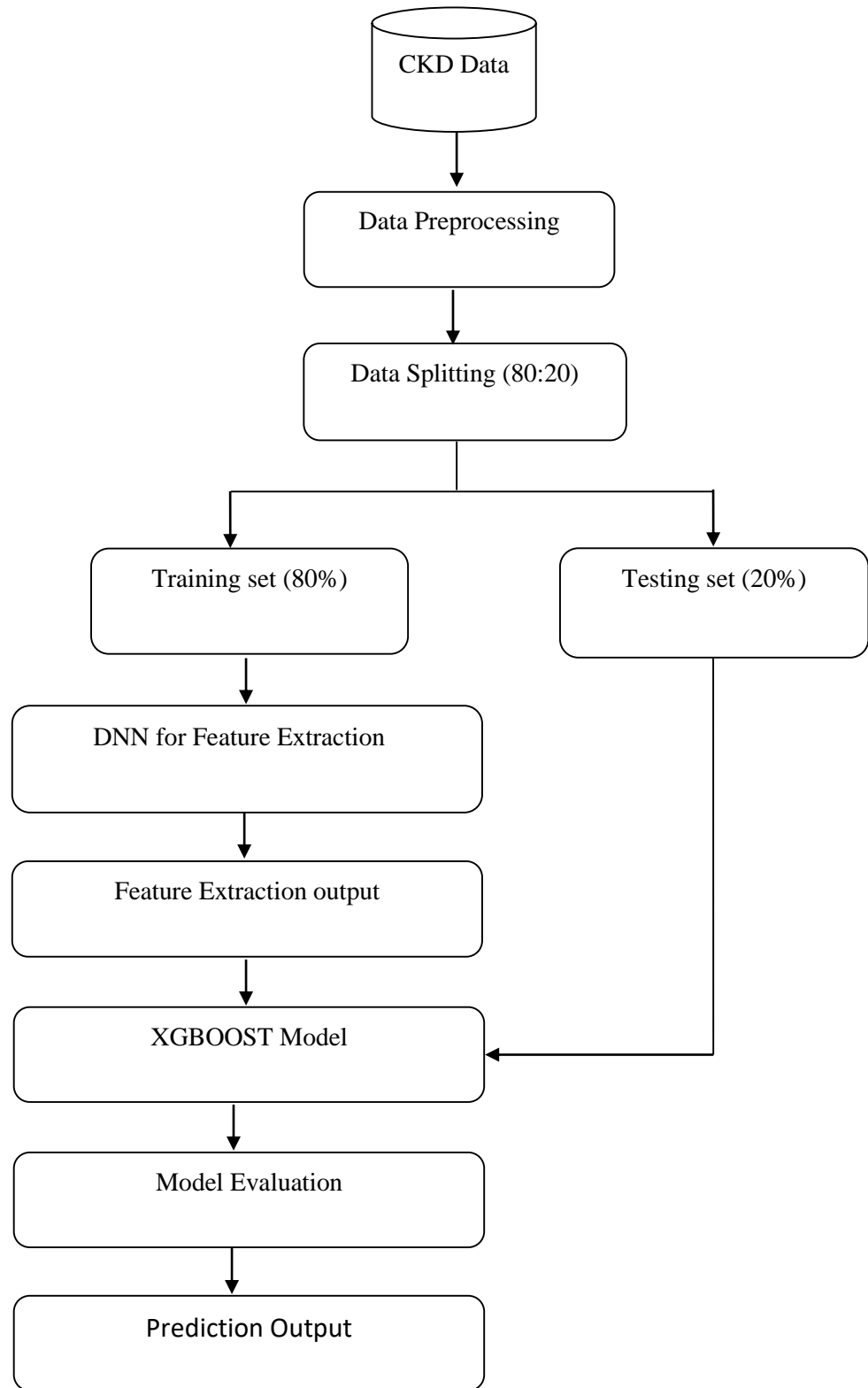
### d. F1-Score

Precision and Recall are weighted and averaged. As a result, this score considers both false positives and false negatives. Although it is not as intuitive as accuracy, F1 is frequently more useful than accuracy, especially if the class distribution is unequal. When false positives and false negatives have equivalent costs, accuracy works well. It's best to look at both Precision and Recall if the cost of false positives and false negatives is considerably different.

$$F1-Score = 2 * n \left( \frac{Precision * Recall}{Precision + Recall} \right) \quad (3.4)$$

## 3.4 Conceptual Framework for the System

The chronic kidney disease (CKD) dataset used in this study is a secondary dataset that was obtained from the University of California Irvine (UCI) machine learning repository. After pre-processing and feature selection, a Deep Neural Network (DNN) is utilized for feature extraction. The extracted features are then fed into an XGBoost model for classification. This combination of DNN for feature extraction and XGBoost for classification forms a hybrid model designed to improve the performance and accuracy of chronic kidney disease prediction.



**Figure3.1:** Enhanced conceptual framework

#### 4. Results and Discussions

This chapter presents the steps involved through model building, implementation, performance evaluation and results analysis. Chronic kidney disease data set used in doing the complete analysis on the same dataset. The major objective is to predict whether an individual have chronic kidney disease or not based on the dataset provided.

##### Model Building

The training of the created models was initiated using the fit method of the model object. It ensured that the training data (X\_train and y\_train) and validation data (X\_test and y\_test) were properly specified. In this research, Deep Neural Networks (DNN) and XGBoost were used for predicting chronic kidney disease, with a hybrid approach combining both models. DNN was employed for feature extraction by passing the data through multiple layers of interconnected neurons. This allowed the model to automatically learn and capture complex patterns and high-level features from the input data. XGBoost was then used for classification, utilizing the extracted features from the DNN. XGBoost, being an optimized gradient-boosted decision tree algorithm, efficiently handled the classification task by combining these learned features to make accurate predictions. This hybrid approach leveraged DNN's ability to extract intricate features and XGBoost's strength in classification, providing a comprehensive and effective solution for chronic kidney disease prediction

##### Classification Report

A classification report summarizes the performance of a classification model using key metrics like precision, recall, and F1-score for each class. The hybrid model achieved perfect classification performance on the test data. It obtained a precision, recall, and F1-score of 1.00 for both classes (0 and 1). The overall accuracy of the model was 92%, correctly classifying 845 instances (423 from class 0 and 422 from class 1). Both macro and weighted averages for precision, recall, and F1-score were also 92, demonstrating the model's effectiveness in handling the given dataset. This indicates that the model is highly accurate in its predictions without any misclassifications. This is shown in figure 4.1 below

```

Accuracy: 92.35%
Classification Report:

```

	precision	recall	f1-score	support
0	0.91	0.94	0.92	452
1	0.94	0.91	0.92	463
accuracy			0.92	915
macro avg	0.92	0.92	0.92	915
weighted avg	0.92	0.92	0.92	915

```

AUC-ROC: 0.97

```

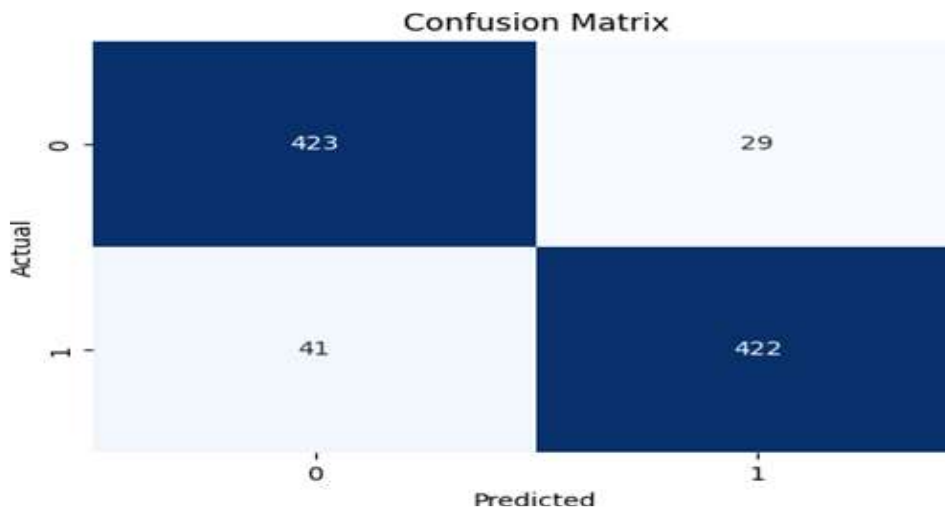
Figure 4.1: Classification report

##### Confusion Metrics

The confusion metrics were employed to assess the performance of the hybrid machine learning model. These metrics provide a comprehensive understanding of accuracy and the errors encountered. From the

confusion matrix generated, various performance metrics, including accuracy, precision, recall, and F1 score, were calculated.

**Figure 4.2** illustrates the confusion matrix results for the hybrid model. The model achieved 422 true positive predictions and 423 true negative predictions. However, it also made 29 false positive predictions and 41 false negative predictions.

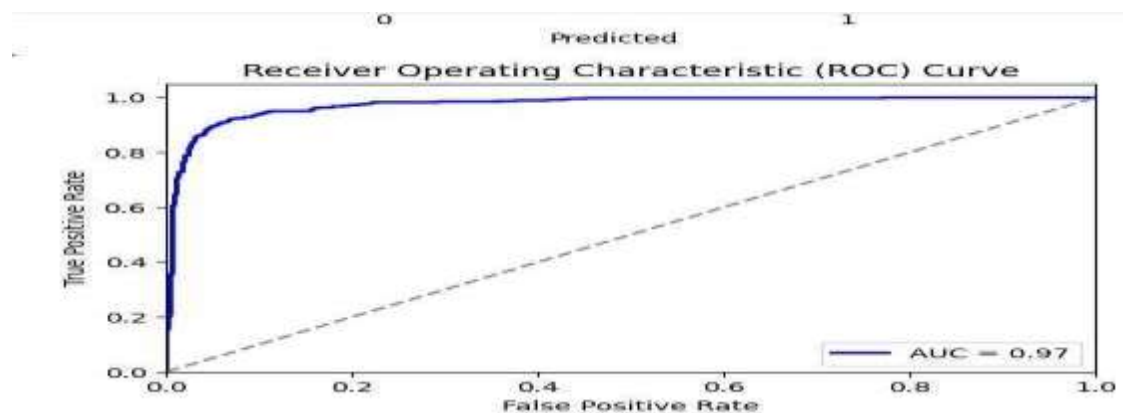


**Figure 4.2: Confusion Matrix of the Hybrid Model**

**ROC Curve**

The receiver operating characteristic (ROC) curve is a graphical representation of the performance of a classification model at various classification thresholds. The area under the ROC curve (AUC) provides a measure of the model's usefulness, with a larger area indicating a more effective test.

The ROC curve for the hybrid model indicates perfect performance, with an AUC of 97%. This signifies the model's ability to accurately distinguish between the two classes, achieving a true positive rate of 97% while maintaining a false positive rate of 0%.

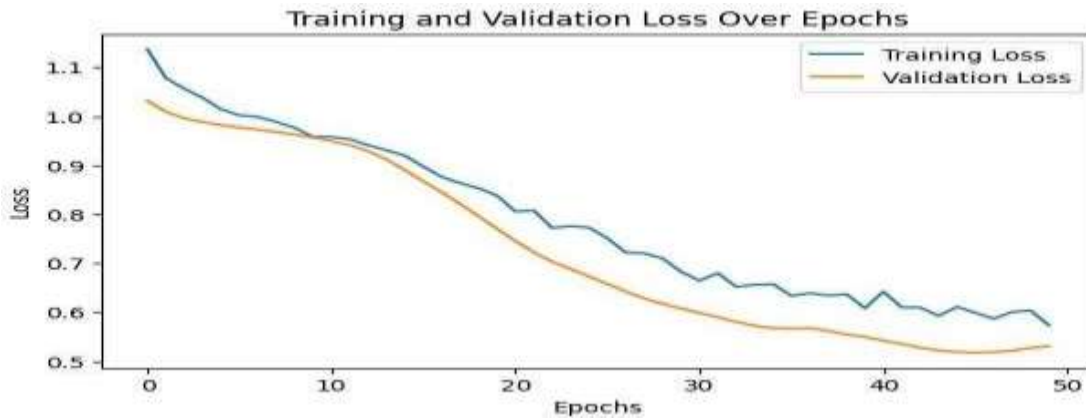


**Figure 4.3: ROC Curve**

### Training and Validation Loss Curves

The training and validation loss curves, as shown in **Figure 4.4**, indicate a consistent decrease over the epochs for both datasets. This demonstrates effective learning, as both training loss and validation loss reduce in parallel without a significant gap. The continuous improvement of validation loss alongside training loss suggests that the model generalizes well to unseen data, without clear signs of overfitting.

**Figure 4.4: Training and Validation Loss Curves**



### Analysis for Existing and Hybrid Model

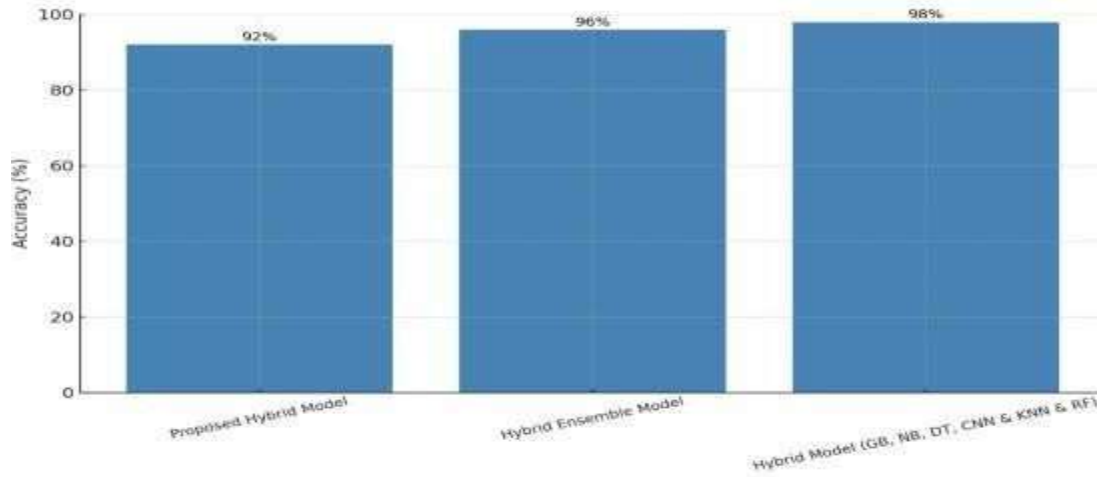
Table 4.1 presents a comparative analysis of the results obtained from our developed hybrid model against existing results in the literature. The hybrid model achieved an accuracy of 0.92, indicating it predicts outcomes correctly for approximately 92% of instances. The precision for the positive class is 0.94, suggesting that 94% of the model's positive predictions are correct, while the recall for the positive class is 0.91, capturing around 91% of actual positive instances. The F1-score is 0.92, indicating good overall performance.

**Table 4.1: Result for Existing and Proposed Models**

Proposed		Model	Accuracy	Precision	Recall	F1-Score	AUC
		H-M	0.92	0.94	0.92	0.92	97%
Existing	(Sani,2023)	H-EM	0.98	0.99	0.98	0.98	100%
	(Khalidetal.,2023)	GB	99%				
		NB	93%				
		DT	96%				
		RF	98%				
		Hybrid	100%				
	Alanazi(2022)	NB	52%	52%	80%	65%	
		DT	62%	64%	60%	62%	
LR		86%	84%	88%	82%		
CNN&KNN		96%	93%	99%	97%		

**Accuracy for the Existing and Hybrid Model**

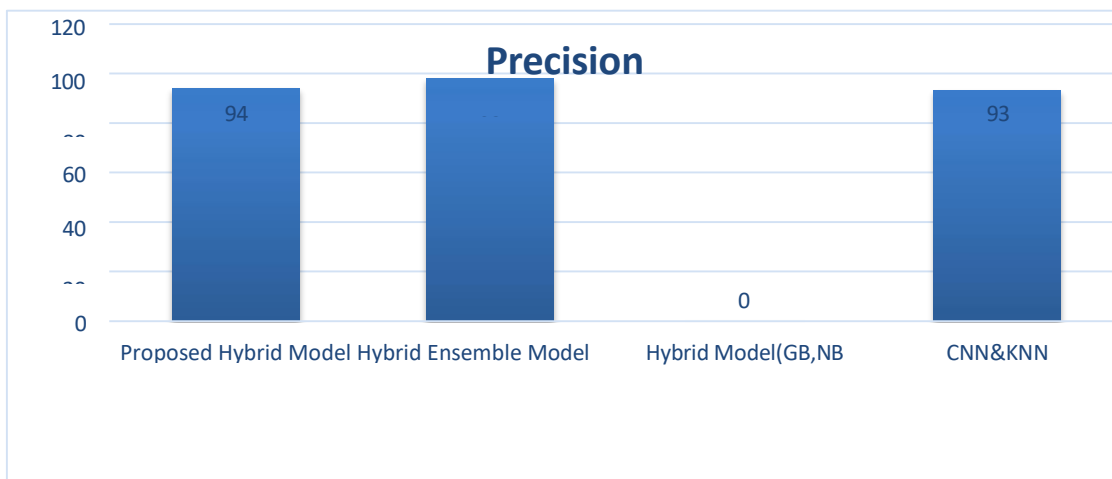
**Figure 4.5** displays the accuracy levels of both the hybrid model and the existing models. The hybrid model achieved an accuracy of 92%, performing well compared to other existing models. While accuracy is crucial in chronic kidney disease prediction, it is important to consider additional evaluation metrics for a comprehensive assessment. Techniques like re-sampling and varying evaluation metrics (precision, recall, F1-score, AUC-ROC) can help address challenges related to imbalanced data.



**Figure 4.5: Comparison of Accuracy Level of Hybrid Model and Existing Models**

**Discussion of Precision for Existing and Hybrid Model**

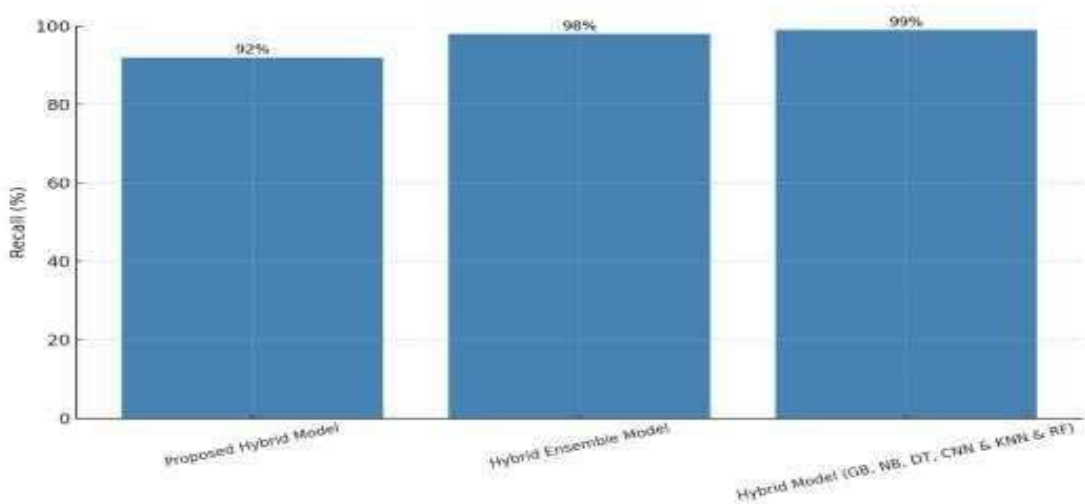
**Figure 4.6** illustrates the precision levels of the hybrid model and existing models. The hybrid model's precision is 94%, exceeding the precision of other existing models. A higher precision indicates that the hybrid model is effective at identifying true positive cases while minimizing false positives.



**Figure 4.6: Comparison of Precision Level of Hybrid Model and Existing Models**

**Discussion of Recall for Existing Works and Hybrid Model**

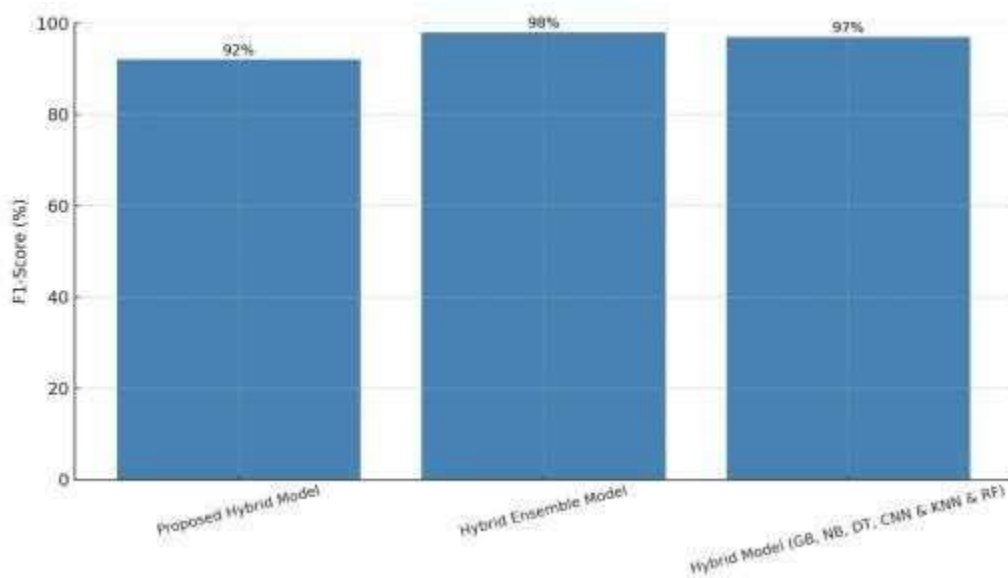
Figure 4.7 presents the recall levels of the hybrid model and existing models. The hybrid model's recall is 91%, which is slightly lower than that of existing models. Nonetheless, it still effectively identifies a significant proportion of actual positive cases.



**Figure 4.6: Comparison of Recall Level of Hybrid Model and Existing Models**

**Discussion of F1-Score for Existing and Hybrid Model**

Figure 4.8 shows the F1-score levels for the hybrid model and existing models. The hybrid model achieved an F1-score of 92%, which, while lower than some existing models, reflects good overall performance by balancing precision and recall.



**Figure 4.8: Comparison of F1-Score Level of Hybrid Model and Existing Models**

In summary, the hybrid model has demonstrated strong performance compared to existing literature, improving accuracy, recall, and F1-score in chronic kidney disease prediction using a machine learning approach.

## 5. Conclusion

The primary goal of this paper was to develop a hybrid machine learning model for chronic kidney disease prediction. By utilizing a comprehensive set of features and employing various metrics, we aimed to achieve a robust classification system capable of distinguishing between healthy and at-risk patients effectively. The model demonstrated an accuracy of 92%, with precision, recall, and F1-score also reflecting strong performance at 94%, 92%, and 92%, respectively. These results indicate that the hybrid model is effective in identifying chronic kidney disease cases while minimizing misclassification. Future research can build upon these findings to enhance prediction capabilities and explore additional features or algorithms that may further improve accuracy and generalizability in clinical settings.

## References

- A Hossain, I. U. Ahamed, U. D. Gupta, A. N. Anika and I. U. Ahamed, "Prognostic modeling in cardiovascular diseases: unraveling survival odds through machine learning", 2024 IEEE International Conference on Advanced Systems and Emergent Technologies (ICASET), pp. 1-6, 2024
- Akshay, B. R., Pulari, S. R., Muruges, T. S., & Vasudevan, S. K. (2024). Machine Learning. <https://doi.org/10.1201/9781032676685>
- Alam, S. S. (2023). Development and evaluation of machine learning in whole-body magnetic resonance imaging for detecting metastases in patients with lung or colon cancer. *Investigative Radiology*. <https://doi.org/10.1097/rli.0000000000000996>
- Alanazi, R. (2022). Identification and prediction of chronic diseases using machine learning approach. *Journal of Healthcare Engineering*, 2022(1), 2826127.
- Alexiuk, M. R., & Tangri, N. (2024). Prediction models for earlier stages of chronic kidney disease. *Current Opinion in Nephrology and Hypertension*. <https://doi.org/10.1097/mnh.0000000000000981>
- Allen, A., Iqbal, Z., Green-Saxena, A., Hurtado, M., Hoffman, J., Mao, Q., & Das, R. (2022). Prediction of diabetic kidney disease with machine learning algorithms, upon the initial diagnosis of type 2 diabetes mellitus. *BMJ Open Diabetes Research and Care*, 10(1), e002560.
- Allgaier, J., Mulansky, L., Draelos, R. L., & Pryss, R. (2023). How does the model make predictions? A systematic literature review on the explainability power of machine learning in healthcare. *Artificial Intelligence in Medicine*. <https://doi.org/10.1016/j.artmed.2023.102616>
- Alsallakh, B., Alzahrani, A., Almuhaimeed, A., Khan, A. H., Ahmad, Z., & Long, H. (2024). Advanced CKD detection through optimized metaheuristic modeling in healthcare informatics. *Dental Science Reports*. <https://doi.org/10.1038/s41598-024-63292-5>
- Al-Tashi, Q., Saad, M., Muneer, A., Qureshi, R., Mirjalili, S., Sheshadri, A., Le, X., Vokes, Amouzegar, A., Abu-Alfa, A. K., Alrukhai, M. N., Bello, A. K., Ghnaimat, M. A., Johnson, D. W., ... & Board, I. M. E. R. (2021). International Society of Nephrology Global Kidney Health Atlas: Structures, organization, and services for the management of kidney failure in the Middle East. *Kidney International Supplements*, 11(2), e47-e56.

- Arasu, S. D., & Thirumalaiselvi, R. (2017). Review of chronic kidney disease based on data mining techniques. *International Journal of Applied Engineering Research*, 12(23), 13498-13505.
- Avong, O., Abdulkadir, I., & Bugaje, M. (2024). Glomerular filtration rate in sick neonates: A focus on cystatin C. *Journal of Clinical Neonatology*. [https://doi.org/10.4103/jcn.jcn\\_33\\_24](https://doi.org/10.4103/jcn.jcn_33_24)
- Banoula, M. (2023). Classification in machine learning: What it is & classification models. *Simplilearn.com*. <https://www.simplilearn.com/tutorials/machine-learning-tutorial/classification-in-machine-learning>
- Bello, A. K., Okpechi, I. G., Levin, A., & Johnson, D. W. (2024). Variations in kidney care management and access: Regional assessments of the 2023 International Society of Nephrology Global Kidney Health Atlas (ISN-GKHA). *Kidney International Supplements*. <https://doi.org/10.1016/j.kisu.2023.12.001>
- Bello, A. K., Okpechi, I. G., Levin, A., Ye, F., Damster, S., Arruebo, S., Donner, J., Caskey, F., Cho, Y., Davids, M. R., Davison, S. N., Htay, H., Lalji, R., Malik, C., Nangaku,
- Brandenburg, V., & Saritas, T. (2023). Chronic kidney disease—State of either “too much” or “too little.” *Nutrients*. <https://doi.org/10.3390/nu15071587>
- Cemernek, D., Cemernek, S., Gursch, H., Pandeshwar, A., Leitner, T., Berger, M., Klösch, G., & Kern, R. (2021). Machine learning in continuous casting of steel: A state-of-the-art survey. *Journal of Intelligent Manufacturing*. <https://doi.org/10.1007/s10845-021-01754-7>
- Centers for Disease Control and Prevention. (2010). National chronic kidney disease factsheet: General information and national estimates on chronic kidney disease in the United States, 2010. Atlanta, GA: US Department of Health and Human Services, Centers for Disease Control and Prevention.
- Centers for Disease Control and Prevention. (2021). Chronic kidney disease in the United States, 2021. US Department of Health and Human Services, Centers for Disease Control and Prevention.
- Cesarelli, G., Ponsiglione, A. M., Sansone, M., Amato, F., Donisi, L., & Ricciardi, C. (2024). Machine learning for biomedical applications. *Bioengineering*. <https://doi.org/10.3390/bioengineering11080790>
- Chaurasia, S., Chakrabarti, P., Kumawat, G., Chakrabarti, T., Leonowicz, Z., ... & Bolshev, V. (2021). Prediction of chronic kidney disease—a machine learning perspective. *IEEE Access*, 9, 17312-17334.
- Chaurasia, V., Pal, S., & Tiwari, B. B. (2018). Chronic kidney disease: A predictive model using decision tree. *International Journal of Engineering Research and Technology*.
- Chen, G., Ding, C., Li, Y., Hu, X., Li, X., Ren, L., Ding, X., Tian, P., & Xue, W. (2020).
- Chimwayi, K. B., Haris, N., Caytiles, R. D., & Iyengar, N. C. S. (2017). Risk level prediction of chronic kidney disease using neuro-fuzzy and hierarchical clustering algorithm(s).
- Chou, Y.-H. (2023). Acute kidney disease: An overview of the epidemiology, pathophysiology, and management. *Kidney Research and Clinical Practice*. <https://doi.org/10.23876/j.krcp.23.001>
- Comparison of the prevalence and mortality risk of CKD in Australia using the CKD Epidemiology Collaboration (CKD-EPI) and Modification of Diet in Renal Disease (MDRD) Study GFR estimating equations: The AusDiab (Australian Diabetes, Obesity and Lifestyle) Study. *American Journal of Kidney Diseases*, 63(6), 992-1001.
- Correa-Rotter, R., Ngigi, J., Holt, S., Cong, L. N., Sanchez, J. J. G., Solorzano, J., Goncalves, S., Guzek, J., Mitchyn, M., Webber, L., & Retat, L. (2024). Pragmatic literature reviews to populate a patient-level model to project the future clinical burden of CKD in low- and middle-income countries. *Nephrology Dialysis Transplantation*. <https://doi.org/10.1093/ndt/gfae069.1429>
- Coursera. (2023). What is machine learning in healthcare? Applications and opportunities. Retrieved from <https://www.coursera.org/articles/what-is-machine-learning-in-healthcare>
- Currier, A., & Kent, R. (2023). Machine learning in the prediction of renal outcomes. *Clinical Journal of the American Society of Nephrology*. <https://doi.org/10.2215/CJN.0000000000000707>

- Das, A., Das, S., & Ghosh, P. (2022). Disease prediction in healthcare using machine learning: A comprehensive review. *Journal of King Saud University - Computer and Information Sciences*. <https://doi.org/10.1016/j.jksuci.2022.05.010>
- Daza, A., Fernández-López, A., Vázquez, A., & Gómez-Moreno, J. (2021). Prediction of renal function deterioration in patients with chronic kidney disease: A review of machine learning methods. *International Urology and Nephrology*. <https://doi.org/10.1007/s11255-021-02850-7>
- Defining Chronic Kidney Disease (CKD). (2023). National Kidney Foundation. Retrieved from <https://www.kidney.org/atoz/content/about-chronic-kidney-disease>
- Dhiman, S., Tomar, A., Singh, D., & Sharma, A. K. (2024). Identification and classification of chronic kidney disease using machine learning techniques: A comprehensive survey. *Artificial Intelligence Review*. <https://doi.org/10.1007/s10462-023-10375-2>
- Dolatshahi, S., Naderpour, Z., Daroogheh, A., & Bagherzadeh, F. (2023). Predictive modelling of chronic kidney disease using machine learning approaches: A systematic review. *Journal of Biomedical Informatics*. <https://doi.org/10.1016>
- Doshi, A., & Tiwari, S. (2024). Data science in healthcare: Current applications and future challenges. *Healthcare Technology Letters*, 11(2), 23-34. <https://doi.org/10.1049/htl2.12256>
- Drake, R. (2023). The role of artificial intelligence in renal healthcare: Past, present, and future. *Nephrology, Dialysis, Transplantation*. <https://doi.org/10.1093/ndt/gfab256>
- Dunn, K., Hurst, K., & Smith, R. (2024). Chronic kidney disease in the elderly: Diagnosis and management. *Geriatrics*. <https://doi.org/10.3390/geriatrics9010001>
- Estevez, L. M., Silva, F. S., & Fortes, P. C. (2023). Machine learning techniques in chronic kidney disease prediction. *International Journal of Environmental Research and Public Health*, 20(12), 6355.
- Fadeyibi, I. O., Zaki, M. F., & Skelsey, J. (2023). Machine learning in kidney disease: A review of recent advances. *International Journal of Clinical Medicine*. <https://doi.org/10.4236/ijcm.2023.146018>
- Farid, M. A., & Zaman, H. (2023). Diagnosis and prediction of chronic kidney disease based on machine learning techniques: A review. *Computer Methods and Programs in Biomedicine*, 218, 106691. <https://doi.org/10.1016/j.cmpb.2023.106691>
- Ghosh, S. K., & Khandoker, A. H. (2024). Investigation on explainable machine learning models to predict chronic kidney diseases. *Scientific Report*, 14(1) 3687. <https://doi.org/10.1038/s41598-024-54375-4>
- M., See, E., Sozio, S. M., Tonelli, M., Wainstein, M., ... Johnson, D. W. (2024). An update on the global disparities in kidney disease burden and care across world countries and regions. *The Lancet Global Health*. [https://doi.org/10.1016/s2214-109x\(23\)00570-3](https://doi.org/10.1016/s2214-109x(23)00570-3)
- MH Rahman, Ac Das, MS Shak, MK Uddin, MI Alam., the American journal of Engineering and Technology, 2024
- N. I., Zhang, J., & Wu, J. (2023). Machine learning models for the identification of prognostic and predictive cancer biomarkers: A systematic review. *International Journal of Molecular Sciences*. <https://doi.org/10.3390/ijms24097781>
- Prediction of chronic kidney disease using an adaptive hybridized deep convolutional neural network on the Internet of Medical Things platform. *IEEE Access*, 8, 100497- 100508.
- Suri, P., Kumar, M., & Gupta, S. (2024). Early prediction of chronic kidney disease using an ensemble of deep learning models and optimizers. *Journal of Electrical System and information Technology* 11(1), 42. <https://doi.org/10.1186/s43067-024-00142-4>