

Applications of Machine Learning and Deep Learning in Nephrology- Chronic Kidney Disease Prediction

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Abstract— Chronic kidney disease (CKD) is a progressive condition where the kidneys lose their ability to filter waste and fluids from the blood, posing a significant global health challenge. As of 2017, CKD affected approximately 753 million people worldwide, contributing to 1.2 million deaths annually. Early detection is critical for timely intervention and effective treatment, but manual analysis often falls short due to limited access to screening and inadequate resources. Leveraging Machine Learning (ML) and Deep Learning (DL) techniques provides a robust solution for predicting CKD at early stages, offering clinicians precise data-driven insights to enhance decision-making. Hence, the aim of this proposed study is to address a critical issue in CKD detection by implementing the ResNet50 model, ResNet50 model using Random Forest Classifier and Vision Transformer for CKD prediction and classification where the models achieve an accuracy of 83.18%, 97.75% and 99.28% providing an effective solution for early diagnosis.

KEYWORDS— Chronic Kidney Disease, ResNet50, ResNet50 with Random Forest Classifier, Vision Transformers

I. INTRODUCTION

Chronic Kidney Disease (CKD) is a progressive condition characterized by the gradual loss of kidney function over time. The kidneys play a crucial role in filtering waste, excess fluids, and toxins from the blood, maintaining overall body homeostasis. When kidney function declines, harmful substances accumulate in the body, leading to severe complications such as hypertension, cardiovascular disease, and kidney failure. In advanced stages, CKD can require dialysis or kidney

transplantation, significantly impacting patients' quality of life.

Early detection of CKD is essential for slowing disease progression and implementing appropriate treatment strategies. However, conventional diagnostic methods, including blood tests, urine analysis, and biopsy procedures, may not always be sufficient for early-stage detection. Medical imaging techniques such as Computed Tomography (CT) scans provide detailed visual representations of kidney structures, aiding in the identification of abnormalities such as cysts, stones, and tumors.

Machine Learning (ML) and Deep Learning (DL) have emerged as powerful tools for automated CKD detection and classification. Traditional diagnostic approaches rely heavily on manual analysis by radiologists, which can be time-consuming, subject to variability, and prone to human error. ML and DL techniques, particularly convolutional neural networks (CNNs) and Vision Transformers (ViTs), offer the ability to process large volumes of imaging data with high accuracy and efficiency. These models can learn intricate patterns within medical images, enabling early and precise classification of CKD into different categories, such as normal, cyst, stone, and tumor.

By leveraging advanced deep learning architectures, automated CKD classification can significantly improve diagnostic accuracy and reduce the burden on healthcare professionals. The integration of AI-driven techniques into medical imaging analysis enhances early detection, supports clinical decision-making, and facilitates timely interventions, ultimately improving patient outcomes and reducing the long-term burden of CKD on healthcare systems.

II. LITERATURE REVIEW

Hridoy, Md Farhan Rakib, et al. (2024) developed a CNN-based model using CT scan images to identify and categorize Chronic Kidney Disease (CKD). Their study evaluated several pre-trained models, including VGG16, ResNet50, and EfficientNetB0, to assess the model's effectiveness in CKD diagnosis and classification. The proposed model demonstrated its potential as a reliable tool for CKD detection.

Jeyalakshmi, G., et al. (2024) developed a Machine Learning-based system utilizing Random Forests for the early detection of Chronic Kidney Disease (CKD). Their approach outperformed traditional methods, highlighting its effectiveness in CKD prediction. However, a potential limitation of the system is its dependence on large, high-quality datasets for training, which may not always be readily available in real-world clinical settings.

Bittencourt, Jalila Andréa Sampaio, et al. (2024) evaluated 196 adult patients, finding that 12.24% had Chronic Kidney Disease (CKD), with 45.8% of them also diagnosed with metabolic syndrome (MS). Their study employed the KNN algorithm for MS screening, demonstrating its effectiveness with notable specificity and sensitivity.

Satukumati, S. B., & Bhat, M. N. (2024) developed a fuzzy neural algorithm for predicting Chronic Kidney Disease (CKD) by analyzing patient data, aiding in early detection. While the approach leverages the strengths of both fuzzy logic and neural networks, a key drawback is its complexity in training and interpretation. The computational intensity and difficulty in tuning, especially with large datasets, pose challenges for practical implementation.

Azizah, M. F., & Paramitha, A. T. (2024) explored the effectiveness of the Gaussian Naive Bayes algorithm for predicting Chronic Kidney Disease (CKD). Their study highlighted the algorithm's potential in CKD prediction; however, a key limitation is its assumption of feature independence, which may not hold in real-world data. When features are highly correlated, the model's performance can be compromised, leading to suboptimal predictions.

Dharmarathne, Gangani, et al. (2024) utilized explainable machine learning to enhance Chronic Kidney Disease (CKD) diagnosis, employing XGBoost for high accuracy and SHAP/PDP for interpretability. While their approach improves model transparency, SHAP and PDP can be computationally expensive, may oversimplify feature interactions, and face challenges with scalability and interpretability in complex or high-dimensional models.

Vidhya, S., & Balachandar, S. (2024) employed machine learning techniques, specifically Support Vector Machines (SVM) and Decision Trees, to predict the presence and severity of Chronic Kidney Disease (CKD) using a dataset of 400 patient records with 14 attributes. While their approach demonstrated effectiveness, SVM can be computationally expensive and difficult to interpret, whereas Decision Trees are prone to overfitting and instability when handling complex relationships in medical data.

III. METHODOLOGY

In this study, we focus on the classification of chronic kidney disease into four distinct categories using advanced deep learning techniques, specifically leveraging the ResNet50 convolutional neural network (CNN), ResNet50 combined with a Random Forest classifier, and Vision Transformers (ViTs). Our dataset comprises 12,446 CT scan images of kidneys, with 5,077 images representing normal cases and the remaining 7,369 corresponding to various kidney disease conditions, categorized into cyst, stone, and tumor. The distribution includes 3,709 cyst images, 1,377 stone images, and 2,283 tumor images. This balanced dataset ensures that the model can effectively learn from a variety of examples, facilitating accurate classification.

To prepare the dataset for model training, we divide it into training, validation, and test sets using an 80:10:10 ratio. In this configuration, 9,956 images are allocated for training the model, while 1,245 images are used for validation, and 1,245 images are designated for testing. This split is crucial as it helps assess the model's ability to generalize its predictions to new, unseen data while ensuring a robust evaluation framework.

The methodology begins with preprocessing the kidney CT images, which includes essential steps such as resizing, noise reduction, and data augmentation. The images are resized to 224×224 pixels to ensure compatibility with deep learning architectures. A median filter is applied for noise reduction, enhancing image quality by smoothing out intensity variations. Data augmentation techniques such as rotation, vertical flipping, shear transformation, contrast adjustment, and reflection are employed to increase dataset diversity and improve model robustness.

The methodology employs ResNet50 CNN for the classification of chronic kidney disease in CT scan images. ResNet50 is a widely used deep learning architecture known for its depth and residual learning capabilities, which enhance feature extraction and mitigate the vanishing gradient problem. In our approach, we utilize ResNet50 in its pre-trained form, leveraging its ability to recognize essential patterns from CT scan images without requiring extensive preprocessing. The model's architecture consists of multiple convolutional layers with residual connections, followed by fully connected layers, enabling it to classify key features associated with kidney disease.

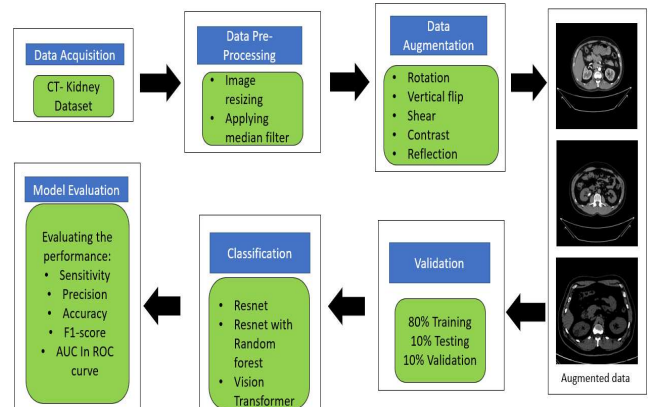


Fig1. Proposed Block Diagram

Fig1. Represents the Block Diagram of the Proposed methodology.

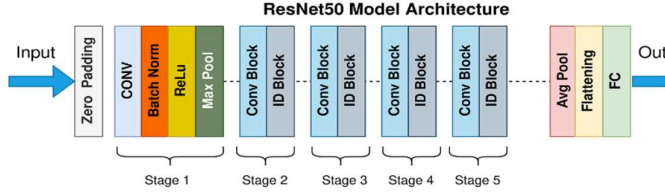


Fig2. ResNet50 Architecture

Fig2. Represents the architecture of the ResNet50 CNN. ResNet50 consists of 50 layers with trainable parameters, including convolutional layers, residual blocks, and fully connected layers. The architecture utilizes 3×3 and 1×1 convolution filters to capture intricate details. Batch normalization and ReLU activation are applied to improve training stability and non-linearity. After feature extraction, the fully connected layers process the information for classification. The architecture's depth and skip connections allow for improved accuracy in classifying chronic kidney disease patterns in CT scans.

In addition to ResNet50, we employ an alternative method where we replace the fully connected layers with a Random Forest classifier. This approach aims to enhance classification performance by combining deep feature extraction with traditional machine learning techniques. By removing the fully connected layer of ResNet50 and using its extracted features as input to a Random Forest classifier, we leverage the strengths of both deep learning and ensemble learning for improved classification accuracy.

We also utilize Vision Transformers (ViTs) for classification. ViTs are an advanced deep learning framework designed for image classification tasks using self-attention mechanisms. Unlike CNNs, ViTs process images as a sequence of patches, capturing long-range dependencies and enhancing feature representation. By leveraging the strengths of self-attention mechanisms, ViTs classify the kidney CT scan images into four categories: normal, cyst, stone, and tumor. The transformer-based approach allows for a more robust feature extraction process, leading to improved classification accuracy.

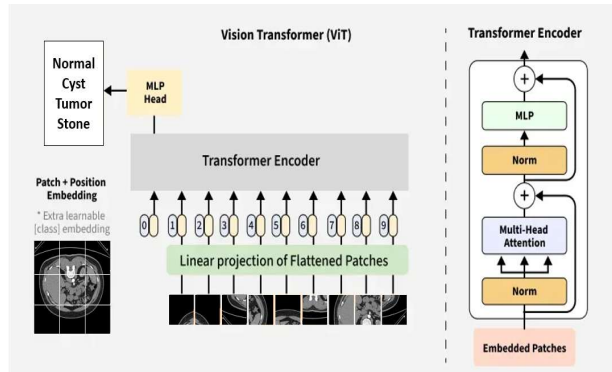


Fig3. Vision Transformer Architecture

Fig3. Represents the architecture of Vision Transformers (ViTs). ViTs divide input images into non-overlapping patches and pass them through a linear projection layer, embedding positional information. The core consists of multiple transformer encoder layers, each comprising self-attention mechanisms and feedforward networks. After feature extraction, a classification head is applied for the final prediction. The ViT model's ability

to process spatial relationships globally makes it highly effective for complex image classification tasks, including chronic kidney disease classification.

During the training process, several critical parameters are carefully tuned, including the learning rate, batch size, number of epochs, and optimizer settings, to optimize model performance. The categorical cross-entropy loss function is chosen to handle the multi-class classification problem effectively, while accuracy serves as the primary evaluation metric.

Following the training phase, the models are validated using the 1,245 images in the validation set and further tested on 1,245 images from the test set. This step is vital for assessing how well the models generalize to unseen data and ensuring their reliability in classifying CT scan images accurately. The output of the models indicates whether a kidney CT scan image belongs to the normal category or one of the kidney disease classes.

Overall, this methodology integrates the strengths of ResNet50, Random Forest classifiers, and Vision Transformers to provide a robust framework for the classification of chronic kidney disease. By combining deep feature extraction and transformer-based models, this approach aims to enhance diagnostic accuracy and contribute to early detection strategies in clinical settings.

IV. RESULTS AND DISCUSSIONS

In this proposed study of CKD detection using ResNet50, ResNet50 with Random Forest Classifier and Vision Transformer respectively, the source images are given and the output is predicted successfully with the trained model with the highest accuracy.

For classification into four classes, the ResNet50 CNN based model has been first trained and the performance of the model has been evaluated using the test data. Confusion matrix is obtained and the plot of Training Accuracy vs Validation Accuracy and Training loss vs Validation loss has also been obtained.

Table1. Confusion Matrix for Classification using ResNet50 Model

No. of epochs=30	Predicted Normal	Predicted Cyst	Predicted Tumor	Predicted Stone
	Actual Normal	Actual Cyst	Actual Tumor	Actual Stone
472	16	5	16	
3	331	3	35	
45	33	145	6	
9	46	2	82	

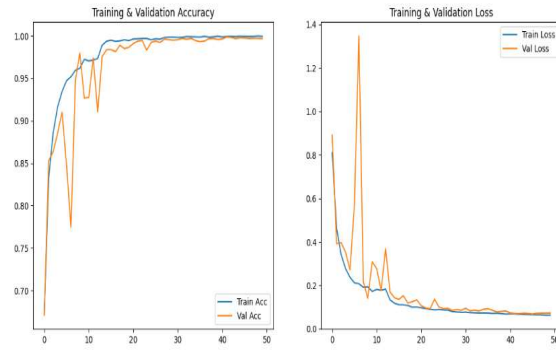


Fig.4. Accuracy and Loss for ResNet50 based CNN Model

Fig.4 represents the Accuracy and Loss plots for the ResNet50 based CNN Model for CKD Classification. The above plots indicate that there has been a little amount of overfitting in training the model.

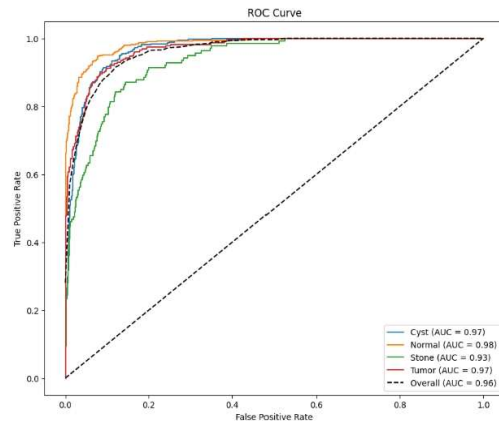


Fig5. ROC Curve for ResNet50 based CNN Model

Fig5. Represents ROC Curve for ResNet50 based CNN Model. The area under the curve here is 0.96 indicating that the model differentiates between the four classes very well.

The ResNet50 based CNN model results in an accuracy of 83.18% and a sensitivity of 0.821.

Next for improving the performance, the fully connected layer of ResNet50 Model is replaced by a Random Forest Classifier. Confusion Matrix is obtained and the plot of Training Accuracy vs Validation Accuracy and Training loss vs Validation Loss have also been obtained for evaluating the performance of the model.

Table-2. Confusion matrix for Classification using ResNet50 with Random Forest

No. of epochs=30	Predicted Normal	Predicted Cyst	Predicted Tumor	Predicted Stone
Actual Normal	505	2	1	1
Actual Cyst	3	366	2	1
Actual Tumor	4	1	223	2
Actual Stone	1	5	1	132

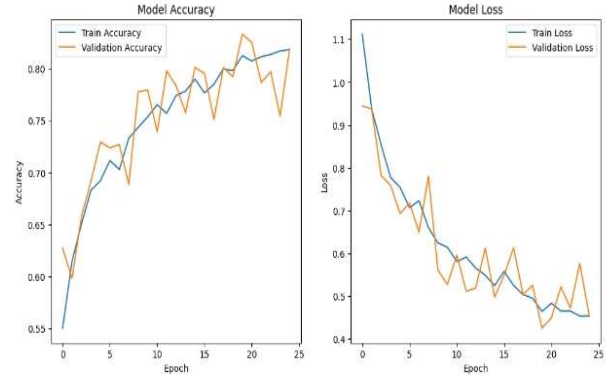


Fig6. Accuracy and Loss for ResNet50 based CNN Model with Random Forest Classifier

Fig.6 Represents the Accuracy and Loss plots for the ResNet50 based CNN Model for CKD Classification. The above plots indicate that there has been a negligible amount of overfitting in training the model.

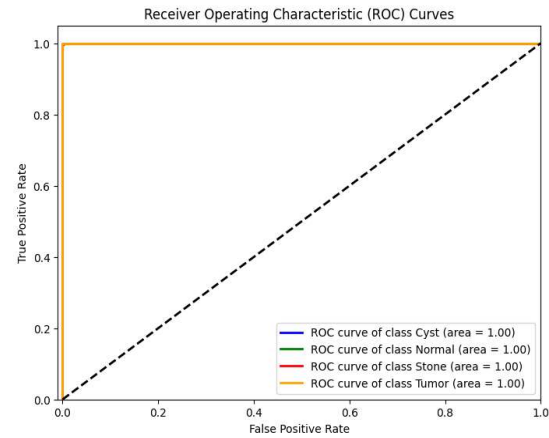


Fig7. ROC curve for ResNet50 based CNN Model with Random Forest Classifier

Fig7. Represents ROC Curve for ResNet50 based CNN Model. The area under the curve here is approximately 1.00 indicating that the model differentiates between the four classes very well without any faults.

The ResNet50 based CNN model with Random Forest Classifier results in an accuracy of 97.75% and a sensitivity of 0.971.

For further improving the performance, the model of Vision Transformers has been used to classify the images into four classes of CKD. Confusion Matrix is obtained and the plot of Training Accuracy vs Validation Accuracy and Training loss vs Validation Loss have also been obtained for evaluating the performance of the model.

Table-3. Confusion matrix for Classification using Vision Transformer

No.of epochs=30	Predicted Normal	Predicted Cyst	Predicted Tumor	Predicted Stone
Actual Normal	372	0	0	0
Actual Cyst	0	509	0	0
Actual Tumor	1	0	228	0
Actual Stone	2	6	0	131

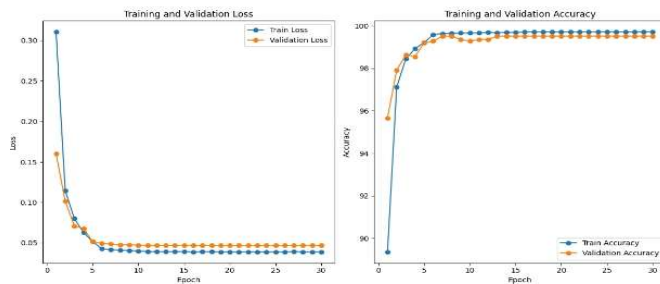


Fig.8. Accuracy and Loss for Vision Transformer

Fig.8 Represents the Accuracy and Loss plots for the vision transformer used CKD classification. The above plots indicate that there is no over fitting at all in the training model.

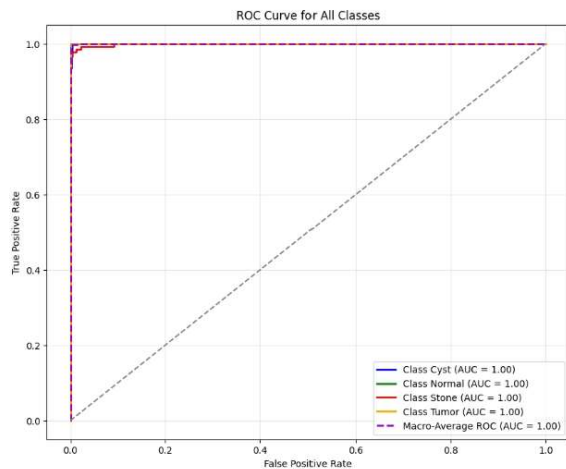


Fig9. ROC Curve for Vision Transformer

Fig9. Represents ROC Curve for vision transformer model. The area under the curve here is 1.00 indicating that the model is best in differentiating between four classes very well.

V. CONCLUSION

In conclusion, we employed ResNet50, ResNet50 with a Random Forest classifier, and Vision Transformers to classify chronic kidney disease from kidney CT images accurately. The training dataset comprised 80% of the total 12,446 images. The efficacy of each model was evaluated using various performance metrics, and the results were compared. Among the models, the Vision Transformer demonstrated superior performance, achieving an impressive accuracy of 99.2% and sensitivity value of 0.9928. The results indicate that the Vision Transformer provides a highly effective solution for CKD classification, outperforming other models and highlighting its potential for aiding clinical diagnosis.

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