Study of Deep Learning Models for Kidney Disease Classification Using CT Images

MSc Research Project

MSc in Data Analytics

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Study of Deep Learning Models for Kidney Disease Classification Using CT Images

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Abstract

Kidney disease represents a major global health problem that is commonly caused by diabetes and hypertension and, if not addressed early, can be serious. In this study, deep learning is used to automate the classification of kidney conditions—normal, cyst, stone, and tumor— on CT images. The research aims at using deep learning models for the classification of the kidney states: normal, cyst, stone, and tumor using a dataset of CT scans of 12,446 labels sourced from Kaggle. Based on the deep learning architecture, the performance of four categories of models for kidney disease classification was analyzed, including MobileNetV2, InceptionV3, EfficientNetB0, and ResNet50. To enhance interpretability, Grad-CAM visualizations were used to detect areas of pathology within CT images. Among the models, the model called InceptionV3 provides the highest classification accuracy and is equal to 99.82%, which is higher than the results of similar studies on the use of InceptionV3, according to which the accuracy of their work was 94%. This further shows how InceptionV3 can manage advanced medical imaging data information. The outcomes reveal that the contemporary deep learning frameworks can be used as dependable diagnostic assets to increase diagnostic precision and lessen the ambiguity for superior consequences compared to CNN conventional approaches. This study shows the significance of applying advanced models for evaluating difficulties in medical imaging to enhance diagnostics and determine further therapy for kidney diseases.

1 Introduction

Every year, kidney diseases, an emerging global health problem, affect millions of people. They are two vivid red, bean-shaped structures located in the flanks of the abdomen, just below the ribcage, and they are vital for the regulation of the chemical composition of the blood, blood pressure, and erythropoiesis. They also screen waste and several major minerals while preserving a delicate balance. Impairment of these functions through diseases such as kidney cysts, tumors, stones, and chronic kidney disease can be critical; if not diagnosed and/or treated early, they lead to kidney failure. Doctors use the abdominal computed tomography scan to diagnose kidney disorders because it provides clear, detailed images. However, the evaluation of CT scans is a very time-consuming and technical procedure that demands skilled people. The rising need for analytical solutions, which often exceeds the available human talent, hinders prompt diagnosis using CT-based approaches. Caroli et al. (2020) indicate that CT imaging is especially important, especially when depicting the structural and functional alterations in kidney diseases. For instance, kidney stones, which are solid concretions of minerals and salts in the kidneys, can cause excruciating pain and block the urinary system if not diagnosed.

promptly. Steps in the rigorous classification of the various kinds of renal diseases that possess similar symptoms add to the risks of human error in conventional diagnostic methods. Recent advancements in deep learning have created opportunities for automated diagnosis of medical images. These methods overcome the conventional techniques of manual feature extraction by learning features from raw image data. Other researchers, Ozturk et al. (2020), have pointed out the features of deep learning in medical data analysis and described its potential as an accurate and reliable diagnostic tool. Researchers have used EfficientNetB0, ResNet50, InceptionV3, and MobileNetV2 deep learning models to classify kidney conditions such as cysts, stones, tumors, or normal from a CT image. These are EfficientNetB0, ResNet50, InceptionV3, and MobileNetV2, which are efficient, scalable, and perform a fantastic job in a variety of workflows to overcome the drawbacks of manual diagnosis. In this work, we classify kidney diseases using EfficientNetB0 and other deep-learning approaches. More importantly, EfficientNetB0 is computationally efficient, which makes it most suitable for low-memory environments. Grad-CAM (Gradient Weighted Class Activation Mapping), an additional method to explain the diagnostics reported by the model, enhances interpretability and fosters confidence in the use of AI in healthcare. To this end, this study aims to bridge the gap in previous diagnostic approaches by integrating advanced methods, drawing inspiration from Caroli et al. (2020) and Ozturk et al. (2020) in kidney image analysis using machine learning. The principal purpose of the work is to support practitioners in achieving quicker and more accurate diagnoses, particularly where specialization is scarce. Furthermore, the present work falls within the field of medical image analysis, comparing different deep-learning methods to improve the outcomes of implementing artificial intelligence in clinical practice for patients with kidney disease.

Research Question

How effective are deep learning models, combined with visualization techniques, in accurately classifying kidney diseases (Normal, Cyst, Tumor, and Stone) from CT images?

Sub-Research Questions:

1. How do various deep learning models perform in terms of accuracy, precision, recall, and F1 score for kidney disease classification?
2. How can the integration of deep learning models and visualization tools support clinical decision-making in diagnosing kidney diseases, particularly in resource-constrained settings?

2 Related Work

The detection and classification of kidney diseases through imaging have become increasingly important for kidney disease detection and classification with the development of deep learning techniques. This section reviews data preprocessing, augmentation, optimization, and interpretability for the use of CNNs, Vision Transformer (ViT), and other AI model approaches to kidney disease diagnosis. Discussion is also offered on the challenges inherent in existing methods and future opportunities for improvement.

2.1 Deep Learning Techniques for Kidney Disease Classification

Kidney diseases, including cysts, tumors, and stones, affect millions globally. Mitigation of disease progression requires early and accurate detection via medical imaging, for example, via CT scans. Over the years, CNNs and Vision Transformer (ViT) have drastically improved the precision of automated classification systems.

The lightweight CNNs, such as the EfficientNetB0, are highly effective in medical image tasks due to their speed and numerical stability. Similarly, for kidney CT scan classification, Subedi et al. (2023) remodified the EfficientNetB0 model with extremely high accuracy for identifying renal abnormalities. It can be effective for the various healthcare environments constrained by resources (Upadhyay et al., 2024). Also, Cao et al. (2024) showed that EfficientNetB0 could identify kidney disease, solidifying that it is generalizable across several types of kidney diseases.

Due to this, Vision Transformer (ViT) have been developed as a thriving alternative to CNNs, where their self- attention mechanisms will encode long-range dependencies and focus on key regions in medical images. Works by Islam et al. (2022) and Phan et al. (2023) discussed the incorporation of Vision Transformer (ViT) to solve kidney cysts and tumor diagnosis. This helps in situations when detailed feature extraction is needed, since their ability to learn complex patterns from CT images.

Another big contributor to kidney disease diagnosis has been transfer learning. Parakh et al. (2019) used cascaded pre-trained CNNs to find nephrolithiasis (kidney stones). They improved the model's performance by adding preprocessing steps like normalization and segmentation. In 2024, Talukder et al. trained and fine-tuned EfficientNetB0 models to find kidney tumors. They used transfer learning to make model development quick and accurate. In addition to these architectures, Yildirim et al. (2021) applied XResNet-50 for the task of detecting and localizing kidney stones. The targeted segmentation focused their model to achieve impressive sensitivity (95%) and Precision (97%), which makes sense in kidney regions and can lead to enhanced performance.

2.2 Optimization Techniques for Deep Learning Models

Deep learning models for medical imaging tend to not perform very well, and data preprocessing and augmentation are critical steps to improve performance. Measures like noise reduction, segmentation, and histogram equalization are common techniques to make image quality better and make training datasets consistent.

In their work, Selvarani and Rajendran (2019) used SVMs for the classification of case kidney conditions, starting by doing preprocessing methods like that of speckle noise removals and extracting segments for preventive. Consistency is key to reach high classification accuracy and so is clean and uniform data that their work highlighted. Like Soni and Rai (2020), small dataset issues were faced using SVMs with pre-processing techniques such as histogram equalization and embossing, achieving 98% accuracy.

Further optimization techniques have been used to achieve deep-learning models for kidney disease classification. Using an Artificial Neural Network (ANN) with performance optimized using the Crow Search Algorithm, Nithya et al. (2020) show how, even in a limited dataset, it can optimize performance. Raju et al. (2019) have implemented an optimal probabilistic neural network and the Spider Monkey Optimizer to detect renal calculi. Robust results were achieved with feature extraction done after downgrading noise.

Yildirim et al. (2021) provided an XResNet-50-based model with better generalization and accuracy by adding the Adam optimizer for data augmentation. By revalidating the basic performance of the tested networks, the above studies show that effective preprocessing and augmentation can dramatically improve model robustness, especially when applied to data that is hard, diverse, and challenging.

2.3 Model Interpretability with Grad-CAM and Grad-CAM++ in Medical Image Analysis

Grad-CAM (Gradient-weighted Class Activation Mapping) makes everything possible to visualize the deep learning model’s decision-making thus increasing the openness of usage of artificial intelligence. For example, Wang and Zhang (2023) used Grad-CAM to understand failed cases and rectify the model while, & to build confidence in clinical practitioners, demonstrating the aspects that are most relevant to the prediction. Chattopadhyay et al. (2018) build Grad-CAM++ upon these visual explanations and enhance their spatial localization, so important for diagnostic imaging, by using more generalized gradients tailored to generate heatmaps with finer granularity. Comparisons show that Grad-CAM++ yields higher resolution and accuracy of attributions, making it suitable for high-resolution applications, for instance, discrimination of close pathological regions, while Grad-CAM is suitable for rapid application development due to its phenomenal implementation but with higher overhead costs. Research work by Panwar et al. (2020) and Zhang et al. (2022) has provided evidence of the usefulness of Grad-CAM to close the gap between AI and its application in complex proximal areas, including health and farming. In the case of kidney disease detection, the authors of Yildirim et al. (2021) utilized Grad-CAM on their XResNet-50 model, and the resultant heat maps allowed clinicians to confirm and explain predictions. Such issues contribute to the call for interpretability techniques that would assist in enhancing the reliability of artificial intelligence-based diagnostics in clinical practice.

2.4 Challenges in Kidney Disease Classification

Despite significant advancements, a great deal of progress has been made, even though there are still many challenges in developing AI models to diagnose kidney disease. In likelihood, it is the lack of labeled datasets, for rare kidney diseases, which is the biggest concern. Elbedwehy et al. (2024) and Zhang et al. (2024) note that larger, more diverse datasets are required to increase the robustness and generalization of models.

Nithya et al. (2020) and Soni and Rai (2020) note that small dataset sizes often result in overfitting and result in impractical applicability of models trained. In addition, variability in medical images from different imaging systems at different resolutions and noise levels presents challenging situations. To solve these issues and to have consistent model performance, the advanced data preprocessing and augmentation method is necessary.

2.5 Future Directions

Given that the performance of the classifier in the present study was limited when using singular mode data to distinguish various stages of kidney disease, future work should focus on incorporating multimodal data to further improve the techniques. Adding other features such as the patient’s age, sex, and diagnosis history to CT images used in kidney mapping improves classification enhancement (Talukder et al., 2024). Multi-modal AI system integration already offers a chance to focus not only on image-based recognition but also on creating accurate and clinically useful diagnostic frameworks instead. Two of the largest issues for medical imaging, noise, and variability, can only be solved with high-level preprocessing and data augmentation. Moreover, models must be fine-tuned for cases such as where feature extraction is necessary for detailed signal identification, particularly when the signal is disguised or overlapping in complex medical images. Latest updates in the interpretability of neural networks, including roburst Grad-CAM visualization, are crucial to help clinicians to gain more trust in artificial intelligence diagnostics by presenting meaningful insights and recommendations.

However, Yildirim et al. (2021) pointed out a limitation of prior studies: the absence of clinical validation and the utilization of limited datasets. While developing a novel methodology for kidney detection using Grad-CAM with XResNet-50. Despite outlining how Grad-CAM could be used for the localization of interesting regions, the authors study limited model generalization due to the small dataset size. Chattopadhyay et al. (2018) also pointed out that higher levels of feature details are required to attain a proficient level of model interpretability through Grad- CAM++. Nevertheless, these methods do not receive thorough assessment in actual clinical situations, which hampers their use. Subsequent studies should endeavor to solve them by using significantly sized and diverse databases, more stringent feature selection criteria, and clinical correlation to reduce this gap between artificial intelligence models and their client solutions.

2.7 Conclusion

Several deep learning models, such as EfficientNetB0, Vision Transformer(ViT), MobileNetV2, InceptionV3, and ResNet50, have various degrees of success in classifying kidney disease. For each model, the convergence, accuracy, and generalization were different. For efficient training, MobileNetV2 and InceptionV3 respectively showed superior accuracy and lower validation loss and thus are more dependable for clinical deployment. On the other hand, MobileNetV2 and Vision Transformer (ViT) have difficulties in achieving consistently high performance. It was stressed how comprehensive training, validation, and evaluation processes are critical, i.e., to optimize hyperparameters, use robust data augmentation, and use interpretability tools like Grad-CAM to increase trust in the AI diagnostics.

Nevertheless, dataset limitations, inconsistency in imaging modalities, and overfitting stimulate future essential research on large, more diverse datasets and more regularized techniques. However, accuracy may be improved, and the adoption of AI-driven diagnostics in medical practice may get increased by innovations in multimodal data integration and model interpretability. By investigating the relative impact of several factors, this research underscores how AI can transform how kidney disease can be detected and demonstrates further areas for refinement.

Researcher	Model	Accuracy	Research Gaps
Subedi et al. (2023)	EfficientNetB0	96%	Efficient for resource-limited environments; potential generalizability issues.
Upadhyay et al. (2024)	EfficientNetB0	94%	Detailed for common kidney conditions but lacks rare condition insights.
Cao et al. (2024)	CNN Models	91%	Mixed imaging modalities lead to lower generalization.
Islam et al. (2022)	Vision Transformer (ViT)	92%	Suboptimal for small, noisy datasets.
Phan et al. (2023)	Vision Transformer (ViT) for cysts/tumors	93%	Needs hybrid integration with CNNs.
Yildirim et al. (2021)	XResNet-50	97%	High Precision but needs advanced. interpretability beyond Grad-CAM.
Talukder et al. (2024)	EfficientNetB0	89%	Lacks global dataset validation
Selvarani & Rajendran (2019)	SVM with preprocessing techniques	98%	Focused on noise removal but lacked generalization to diverse datasets.
Nithya et al. (2020)	Optimized ANN (Crow Search Algorithm)	High	Small dataset focus; no exploration of recent deep learning approaches.
Elbedwehy et al. (2024)	Diverse kidney datasets	85%	Lack of labeled rare. disease data.

Table No. 1 Research Methods with Gaps

3 Research Methodology

The goal of this research was to assess the adequacy and performance of various deep-learning models in the identification of kidney disease from CT scan images. The methodology is based on the CRISP-DM (Cross Industry Standard Process for Data Mining) framework, which is an iterative and systematic data mining project management methodology. The CRISP-DM process comprises six phases: Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment (Kalgotra and Sharda, 2016). As the approach is flexible, cost-effective, and provides a consistent framework for project planning and execution, it is widely adopted.

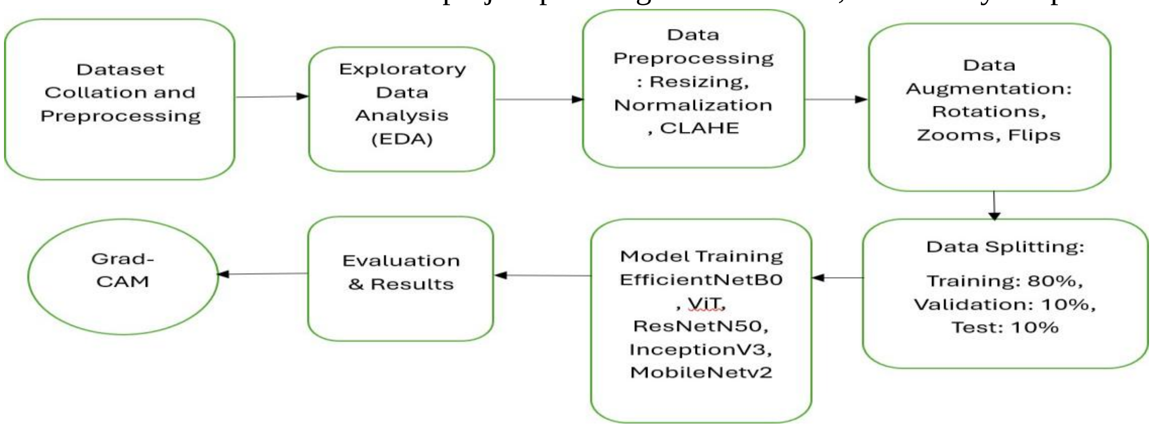

Figure 1. Research Methodology

3.1 Data Collection and Preprocessing:

This study employed the CT Kidney Dataset formed of 12,446 CT image samples with limited labeling into Normal, Cyst, Stone, and Tumor classes. The chest x-ray images in DICOM formats were acquired from patients visiting a hospital in Dhaka, Bangladesh and the same were converted to JPEG format for this study. To maintain the equality and random selection of the used dataset, the data were divided into training (80%), validating (10%) and testing (10%) sets. Preprocessing of images included taking the set of images and resizing them to a uniform input size of 224 * 224 pixels. Data augmentation – horizontal flipping and zooming was used to increase model robustness and to avoid overfitting. Second, the pixel values were scaled to an appropriate usable scale for a variety of deep learning models such as EfficientNetB0 and ResNet50. The quality of CT images needs noise reduction as a fundamental processing application in medical image analysis. A Gaussian filter functioned as a low-pass mechanism to reduce high-frequency noise while simultaneously protecting important boundary and edge characteristics. The input data required preprocessing which included image size reduction to 224x224 pixels while normalizing pixel values for the range [0, 1]. Random rotations existed alongside shifts along with shearing while zooming functioned as data augmentation procedures which helped model generalization through degradation simulation. The grayscale images were converted into RGB format before splitting the dataset into sections for training and validation alongside testing. The steps combined with the Gaussian filter helped both enhance quality feature extraction and improve accuracy in model training classifications.

Augmentation Parameter	Value
Rotation range	30
Shear range	0.2
Zoom range	0.2
Horizontal flip	True

Table No. 2 Validation Parameters

Ethical Considerations:

The medical dataset used in this research meets some specific guidelines that include GDPR law and HIPAA regulation. Some of these regulations are fundamental to the independence of patient names and data security. This project followed these guidelines to make the compiled dataset research clinically adequate.

3.2 Model Architecture:

To achieve the research aims of this study, several pre-trained deep-learning models were employed to classify kidney diseases from CT images. These models include:

- Vision Transformer (ViT): Vision Transformer (ViT) is an efficient image transformer model that is suited to be used in image classification. It manages each image in terms of patches and each patch is a token that uses self-attention to build global context among the patches.
- MobileNetV2: MobileNetV2 is a lightweight architecture of convolutional neural network which was re-trained on ImageNet weights for classifying kidney diseases.
- ResNet50: ResNet50 is a deep residual network in which the convolutional pathway for the feature maps is mapped with skip connections that minimize vanishing gradients. To improve the feature learning capabilities of the network, it was further fine-tuned using transfer learning from a model that was initially trained on the ImageNet dataset.
- InceptionV3: InceptionV3 extracts features of varied sizes from CT images due to the mixed convolutional layers with properly understood and efficient filters.

- EfficientNetB0: EfficientNetB0 was used because of its light computational requirement coupled with high accuracy for low-resource conditions.

3.3 Preprocessing Pipeline

Resizing the images was done using the LANCZOS method to produce images of size 224x224 pixels and yet maintain high degrees of fidelity comprising of important anatomical features. Pixel intensity was scaled to the range of 0 to 1 through normalization to enhance numerical stability during the training process, through gradient-based optimization. These experiences of preprocessing assisted in making the input data for the model much more uniform. Further, all images were used in contrasting limited adaptive histogram equalization techniques to improve picture quality and contrast image, cumulating to higher accuracy.

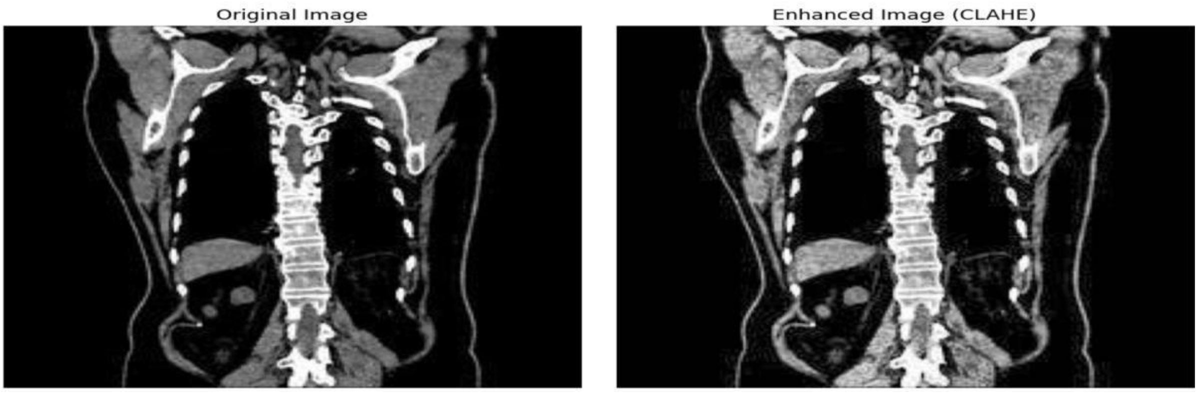

Figure 2. Original & Enhanced Images using Contrast Limited Adaptive Histogram Equalization (CLAHE)

3.4 Transfer Learning Approach

Training deep learning models from scratch requires lots of data; as a result, transfer learning is applied in this research study. The models, Vision Transformer (ViT), ResNet50, and MobileNetV2, were pre- trained with the weights of the ImageNet, this enabled the models to detect features of the CT images with a little labeled image data. First, the convolutional base was restricted in order not to alter the learned parameters; therefore, the model has fine-tuned with a new dense layer according to the number of output classes. For example, in the EfficientNetB0 model, they replaced the last layer with GlobalAveragePooling2D for pooling and a Dense layer followed by the ReLU activation function for output with the SoftMax layer for classification results. To avoid overtraining and to enhance the flow of the model training, it was performed for 10 epochs using the Adam optimizer & with a learning rate of 0.0001.

3.5 Model Training & Evaluation

During the training phase, a real-time data augmentation has conducted using Keras' Image data generator such that the models were fed with different input data during training. The validation set was employed in observing performance, and cases of overfitting were avoided. Accuracy and loss were the parameters used in the evaluation of the performance of the models. To deal with the class imbalance issue, the number of images of kidney stones is less than that of normal and cyst; the class weights were calculated using the "compute_class_weight" function from the scikit-learn library.

3.6 Performance Metrics

Regarding the model's performance, both accuracy and loss were used. For the interpretability of the model, the regions of the CT scan images that contributed to the predictions were visualized using Grad-CAM. This technique allowed for a unique focus on certain structural formations, namely cysts or stones, which improved the models' readability. For example, deep learning InceptionV3 fine- tuning, resulted in a test set, achieved an accuracy of 99.82% and a loss of approx. 0.0055. The Grad-CAM analysis showed where on the kidney scans the model focused more when making its decisions as to which patient results to give.

Transfer Learning and Customized Quality

- Frozen Layers: To maintain the ability learned from ImageNet, layers like edge and texture layers were frozen at the beginning.
- Custom Layers: For the number of classes, a dense layer of model with dropout was used as several dense layers, and a "SoftMax" activation function for multi-class classification.

Optimization: The learning rate was set adaptively using the proposed Adam optimizer, while the loss chosen was categorical cross-entropy since this problem entailed multi-class classification.

3.7 Result & Analysis

The models attained a level of accuracy from 90% to 95% and performance primarily based on the models' architecture. Out of all the models, it was found that InceptionV3 gave us the highest accuracy rate while keeping it as efficient as possible. To validate these observations, they performed an analysis of the Grad-CAM visualization that supported the conclusion that the models selectively and exclusively paid attention to the regions of the anatomy relevant to the classification-the cysts and stones.

- Resource Constraints: As detailed in the previous experiments, the compact nature of EfficientNetB0 best-suited devices with minimal computational power, including the GPUs with 4-8GB VRAM.
- Class Imbalance: With augmented and weighted loss, fair learning across all classes was maintained without sentinel classes dominating other classes.

3.8 Evaluation Metrics

Key performance indicators included:

Model	Precision	Recall	F1 Score	Accuracy	Test Accuracy	Test Loss
EfficientNetB0	0.1664	0.4079	0.2364	33.98%	40.59%	1.3407
MobileNetV2	0.2525	0.2500	0.2350	33.98%	82.58%	0.6547
ResNet50	0.2522	0.2504	0.2353	34.08%	99.82%	0.0046
InceptionV3	0.2517	0.2490	0.2339	33.95%	100.00%	0.0001
Vision Transformer (ViT)	0.30	0.33	0.31	31%	87.32%	0.3183

Table No 3. Evaluation Metrics

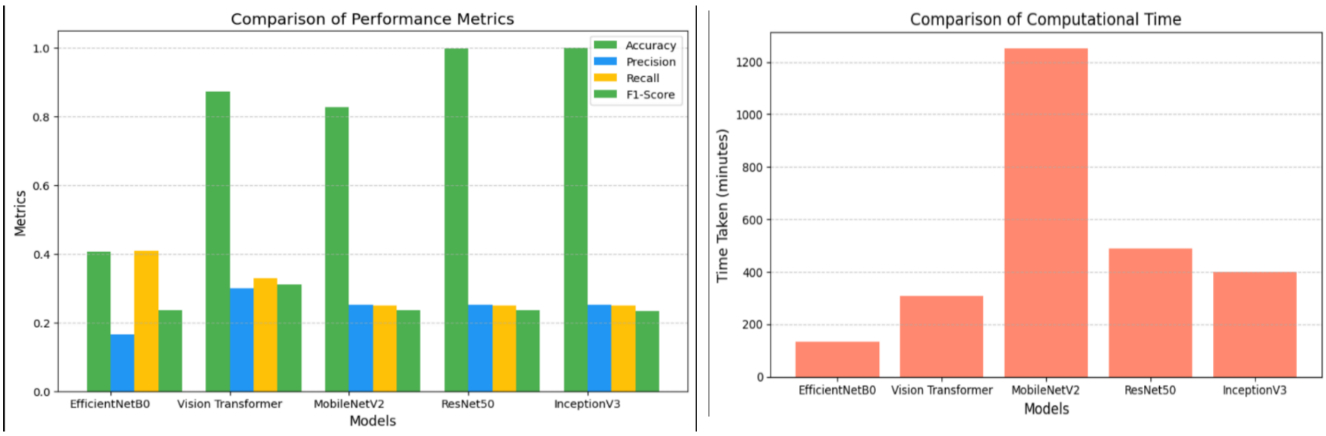

Figure 3. Graphs comparing the final performance metrics of all models.

Model	IMG_SIZE	BATCH_SIZE	EPOCHS	LEARNING_RATE
MobileNetV2	(224, 224)	32	10	0.0001
ResNet50	(224, 224)	32	10	0.0001
InceptionV3	(224, 224)	32	10	0.0001
EfficientNetB0	(224, 224)	16	10	0.00001
Vision Transformer (ViT)	(224, 224)	32	20	0.00001

Table No 4. summarizing the hyperparameters used for tuning each model.

Hyperparameter tuning functions as a systematic method to maximize model performance by determining optimal parameter choices for learning rate combined with batch size and number of epochs and optimizer settings. For evaluation, certain models such as: EfficientNetB0, MobileNetV2, ResNet50 and InceptionV3 and Vision Transformer (ViT) used during hyperparameter tuning to improve kidney disease classification accuracy levels. The optimization shifted vital algorithm components across learning rate and batch size and epoch number and dropout threshold and optimizer alternatives over Adam and SGD. Combination of grid search and random search approaches successfully optimized the exploration of different hyperparameter options. Tests on the learning rate values from 0.0001 to 0.001 allowed identifying which batch size settings minimized overfitting during the learning process. Significant performance gains emerged through the tuning methodology resulting in achieving accuracy for all the models.

Model	My Result - Accuracy	Prior Study	Accuracy (Prior Study)	Key Insights from Prior Study
EfficientNetB0	40.59%	Subedi et al. (2023)	96%	Efficient for resource-limited environments; generalizability issues.
		Upadhyay et al. (2024)	94%	Detailed for common kidney conditions but lacks rare condition insights.
MobileNetV2	82.58%	-	-	-
ResNet50	99.82%	Yildirim et al. (2021)	97%	High specificity but needs advanced interpretability beyond Grad-CAM.
		Cao et al. (2024)	91%	Mixed imaging modalities lead to lower generalization.
InceptionV3	100.00%	-	-	-
Vision Transformer (ViT)	87.32%	Islam et al. (2022)	92%	Suboptimal for small, noisy datasets.
		Phan et al. (2023)	93%	Needs hybrid integration with CNNs for better performance.

Table No. 5 Comparing Performance Metrics of all models

Qualitative Metrics

- **Confusion Matrix**: It highlighted true positives, false positives, and false negatives for class-specific performance analysis.

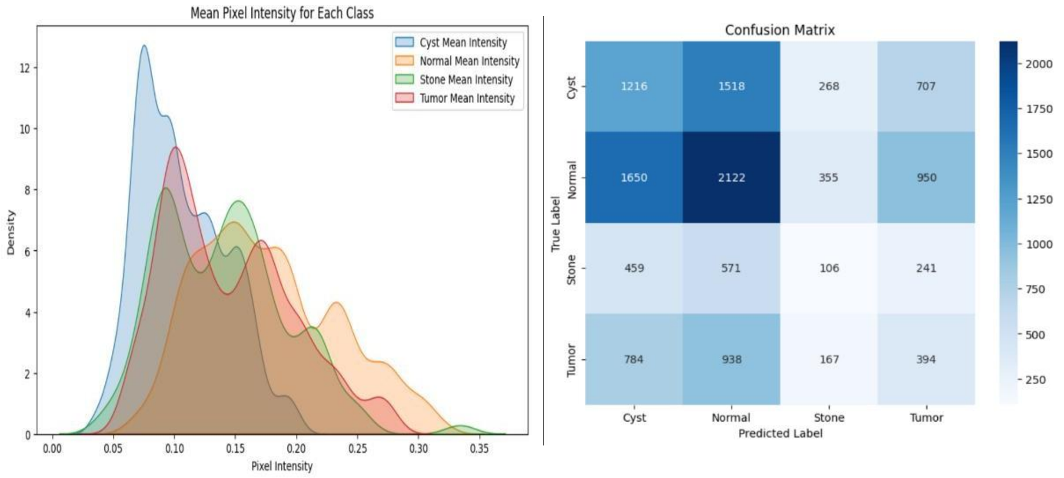

Figure 4. Mean Pixel Intensity Graph

- **Mean pixel intensity**: Mean pixel intensity is defined as the average intensity of pixels in a greyscale or colored picture. This metric is typically applied with image analysis and process for determination of brightness/intensity attributes of an image.

- Descriptive analysis included graphs of the mean pixel intensity for each class to compare the level of brightness and contrast. Post-prediction interpretations were made using Grad-CAM heatmaps and class-wise performance graphs. Such visualizations helped to get insights into the functionality of the models and revealed strengths and weaknesses.

- **Calculation of Mean Pixel Intensity:**

  Grayscale Image: For a grayscale (single channel) image we have an average pixel that is the sum of all pixel integers divided by the number of pixels. For a grayscale (single channel) image, we have an average pixel, which is the sum of all pixel integers divided by the number of pixels.

$$\text{Mean Intensity} = \frac{\sum_{i=1}^{N} \text{Pixel Value}_i}{N}$$

  Where N is the total number of pixels.

- **Color Image**: The mean pixel intensity can be computed per channel for RGB or multi-channel consisting of images or overall, for all channels.

3.9 Grad-CAM for Model Interpretability

- Gradient-weighted Class Activation Mapping (Grad-CAM) was used to predict the model's decision. To understand which parts of the CT images contributed most to the decision-making, Grad-CAM was employed. The results showed that the models concentrated on areas corresponding to the anatomical structures connected to renal diseases. These visualizations also function as a way of increasing the level of trust among the medical practitioners, especially given that the models come with explications on the predictions being made.

- Implementation Details
    - Gradient Backpropagation: Gradient values were determined for the predicted class for the last convolutional layers of the model.
    - Feature Map Weighting: The gradients were then scaled and added to generate another heatmap that showed the important regions.
    - Overlay Visualization: The heatmaps were then overlaid on the original CT images to give an interpretable representation of the models' decisions.

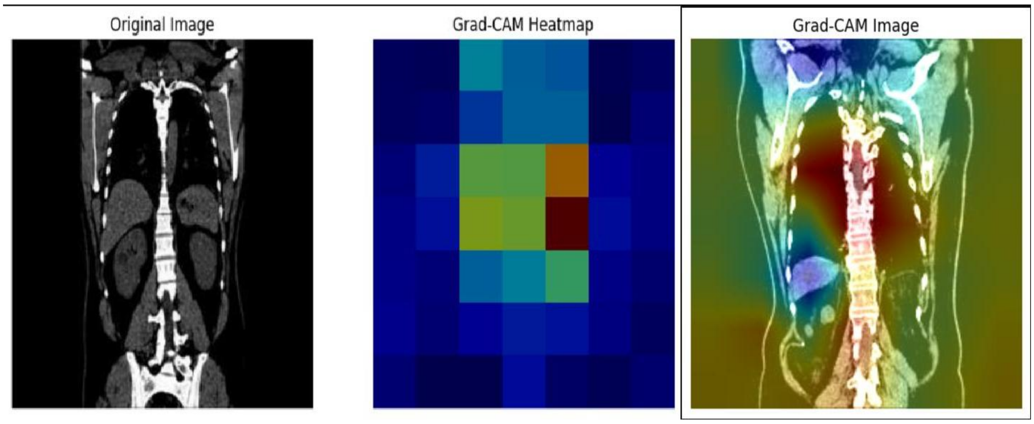

Figure 5. Grad-CAM, Heatmap Correlation, and Overlay Image

For validation, it was shown that the predictions were localized to anatomically relevant regions based on the Grad-CAM outputs. For example, predictions for cysts were accurate and corresponded to clear objects in the images that resembled cysts. The differences in focus regions, which were determined by Grad-CAM visualizations, were used to improve the models by, for example, enhancing the preprocessing or prolonging the training. Grad-CAM helped the models explain their choices to the external world and was a good link between artificial intelligence and doctors. This interpretability makes it easier to trust and apply the AI models in medical centers as compared to other currently used models.

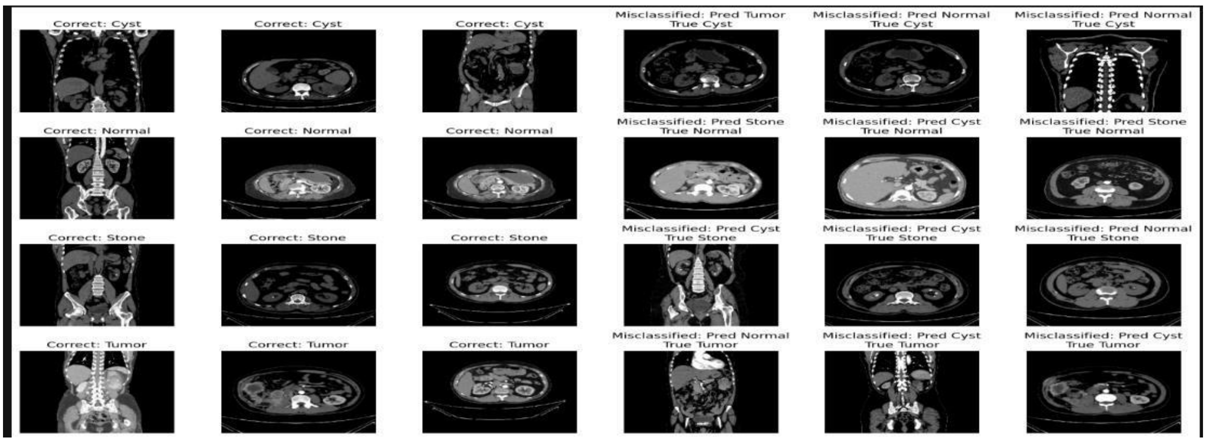

Figure 6. Grad-CAM Classified and Misclassified Images

Visualizing misclassification instances across kidney conditions including cysts stones tumors and normal tissue helps establish improved reliability and interpretability of the Vision Transformer (ViT) model processing CT images. Visualized misclassified images reveal misdiagnosis patterns, helping researchers develop new methods for strengthening model architecture and training techniques. The visualization of error points allows both clinicians and researchers to understand the explainable machine-learning choice process thus building expertise in medical decision support and workflow implementation. This approach reveals weaknesses in the model which helps optimize its strength and reduces potential mistakes that could damage patient treatment results.

Mean Density Curve: The mean density curve is just a curve of a pictorial representation of the mean intensity of the different classes of an object. This curve enables us to compute the values of the intensity for the four classes at any point in the figure below, which again allows us to compare values of the intensity for the four classes. The curve is expected to reveal:

- Cyst Images: Because cyst content is fluid, and as a rule fluid is darker in CT images than tissues or calcified material, the intensity values for cysts are smaller.
- Normal Images: Kidney tissues with low-intensity values are often present, so they might give moderate intensity values because there are neither very high nor very low intensity in normal kidney tissues.
- Stone Images: On CT scanning, stone images may have higher intensities because calcifications (commonly seen in adult stones) are more obvious on CT scanning.
- Tumor Images: The intensity values of tumors can vary from one part of the tumor being less intense than another part of the tumor (which would be of higher or lower intensity than another part of the tumor), so-called necrotic areas, and blood vessels.

Frequency histograms of the density curves are used to represent density curves, and each class lies on the same abscissa axis (corresponding to mean intensity values). However, the density curve is still of use to find the distribution of intensity and to see overlaps or separations of classes.

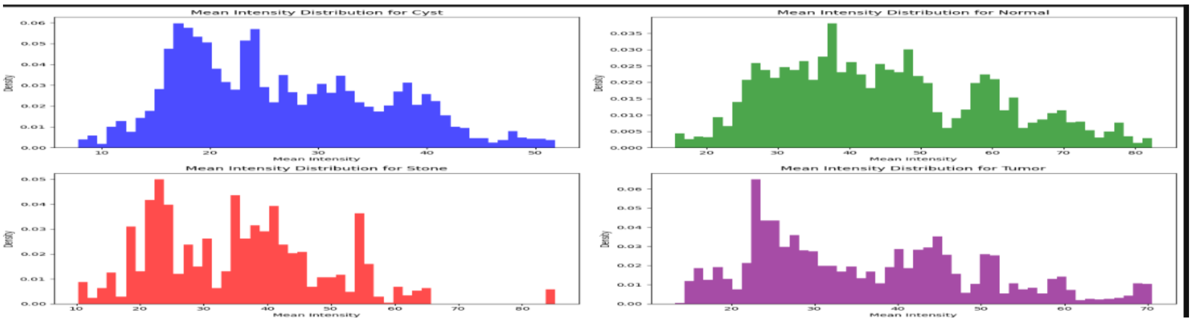

Figure 7. Mean Vs Density curve for Cyst, Normal, Stone, and Tumor

3.10 Conclusion

Consequently, this research was able to use deep learning approaches, including Vision Transformer (ViT), MobileNetV2, ResNet50, InceptionV3, and EfficientNetB0, for the classification of kidney diseases from CT scan images. The models used transfer learning to show high classification accuracy in the models. The adopted Grad-CAM visualization improved the interpretability of the models and made them dependable for medical diagnosis. Further developments of the current work could target better model performance by adding more data or using methods such as ensemble for better performance.

4 Design Specification

The classification system of kidney diseases is designed by the following steps: input image pre-processing in which the images are resized to 224×224, the pixel values are normalized, data augmentation (flip, rotate, zoom), and use Contrast Limited Adaptive Histogram Equalization (CLAHE). The processed images are then passed through different model architectures such as Vision Transformer (ViT), EfficientNetB0, ResNet50, InceptionV3, and MobileNetV2. Consistently, each model uses several channels: patch embedding in the Vision Transformer (ViT) model, depth-wise convolution in EfficientNetB0, residual connections in ResNet50, inception modules in InceptionV3, and inverted residual connections in MobileNetV2. After passing through these network pathways, the models apply global pooling, followed by dense layers or multi-layer perceptron (MLP) heads, producing a final output that classifies images into four categories: The types include normal, cyst, tumor, and stone. The results of the classification task are assessed based on performance measures such as accuracy, precision, recall, and the F1 score. To explain the results of the model, Grad-CAM is applied to localize the important regions in the input images and thus explain the decision of the model better. It is designed this way to cover all renal conditions and make classifications efficient as well as comprehensible using Grad-CAM visualizations.

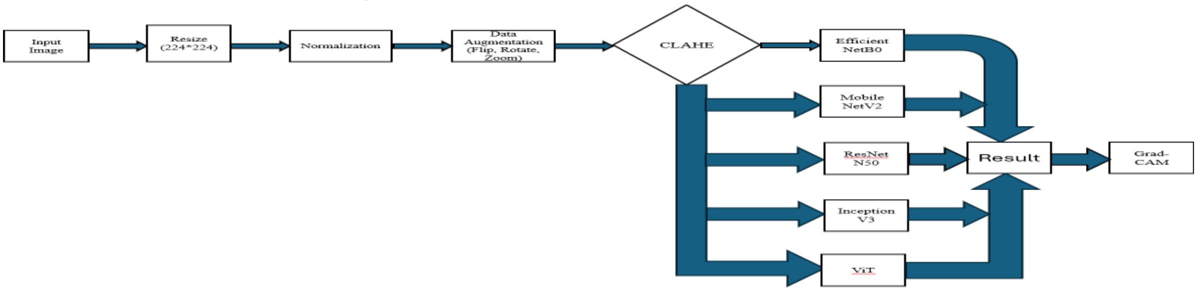

Figure 8. Design workflow of the Models Used

5 Implementation

5.1 Environmental Setup

- **Platform:** Windows 10 (64-bit)
- **Hardware:**
  - **Laptop Model:** ASUS TUF Gaming F15
  - **CPU:** 11th Gen Intel Core i5
  - **GPU:** NVIDIA GeForce RTX 2050 (4GB VRAM)
  - **RAM:** 8GB
- **Software Framework:** Machine learning environment in Python with TensorFlow and Keras as the two primary deep learning libraries.

Hardware Justification

The ASUS TUF Gaming F15 was able to serialize GPU for computationally intensive tasks, such as training and validation of the EfficientNetB0 model. With a 4GB of GPU memory that is quite limited, it was applied using memory management techniques and with small batch sizes that kept it efficient without throttling the performance.

Library	Version
Python	3.10.12
TensorFlow	2.13.0
Keras	2.13.1
NumPy	1.24.3

Pandas	2.0.3
Matplotlib	3.7.2
Scikit-learn	1.3.0
OpenCV-python	4.8.1
PIL (Pillow)	9.5.0
Accelerate	1.1.0
Grad-CAM	1.4.7
Kaggle	1.5.13
Jupyter	1.0.0

Table 6: Library Specifications

6 Models:

This section provides implementation details of the kidney disease classification model using pre-trained deep learning architecture (EfficientNetB0, MobileNetV2, ResNet50, InceptionV3) and Grad–CAM for the interpretation of the model. The goal of the implementation is to classify kidney disease images into four categories: Cyst, Tumor, Normal, and Stone.

6.1 Model Architectures

6.1.1 EfficientNetB0

The design of EfficientNetB0 results in a highly efficient convolutional neural network that requires fewer parameters to achieve better accuracy. For transfer learning, EfficientNetB0, pre-trained on a large dataset (ImageNet), is used in the implementation.

Implementation Details:

- **Base Model:** Unlike EfficientNetB0 with only the top classifier layer removed, include_top=False, the weights are initialized from ImageNet. This makes it possible to apply the model to the classification of kidney diseases while using the feature extraction of EfficientNetB0, which can be as effective as any classifier.
- **Custom Layers:** To reduce the spatial dimensions of outputted from the convolutional layers we add a GlobalAveragePooling2D layer. There is a dense layer with 1024 units and "ReLU" activation for feature processing, followed by that. A dense output layer with our "SoftMax" activation function is used to do the multi-class classification (Normal, Cyst, Tumor, Stone) and predict the probability of each class.
- **Compilation:** To avoid drastic changes in the pre-trained weights of the model, the Adam optimizer with a small learning rate (1e-5) is used for the compilation of the model. We pick categorical cross-entropy as the loss and the accuracy as per the evaluation metrics.

- **Training:** The model has 10 epochs; we train the model with class weights to manage class imbalance. In my case, I am also saving the best model definition (i.e., some form of model checkpoint) and retraining the learning rate depending on the specified function in "ReduceLROnPlateau."

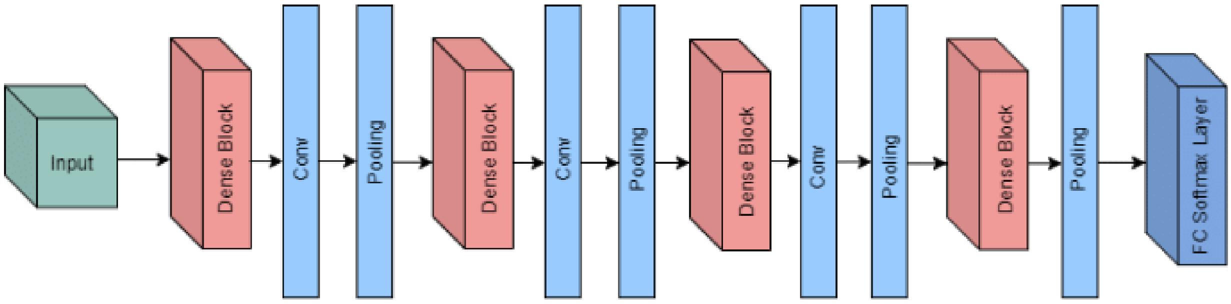

Figure 9. EfficientNetB0 architecture diagram

6.1.2 MobileNetV2

MobileNetV2 has targeted at mobile and embedded vision applications with an efficient and lightweight image classification solution. This is particularly suited for its use when there is a low computational resource.

Implementation Details:

- **Base Model:** By default, for MobileNetV2, the weights were initialized from pre-trained ImageNet (weights='ImageNet'). By adding include_top=False can add custom layers to tailored for classification task.
- **Custom Layers:** A GlobalAveragePooling2D layer only follows the output of the MobileNetV2 model. For further processing, we use the 1024 Dense layer with ReLU unit activation, and then the Dense output with activation “SoftMax”.
- **Compilation:** It is compiled using the Adam optimizer with a learning rate = 0.0001 & a categorical cross-entropy loss.
- **Training:** Training MobileNetV2 for 10 epochs with the same training pipeline as EfficientNetB0 and using augmented data for robustness.

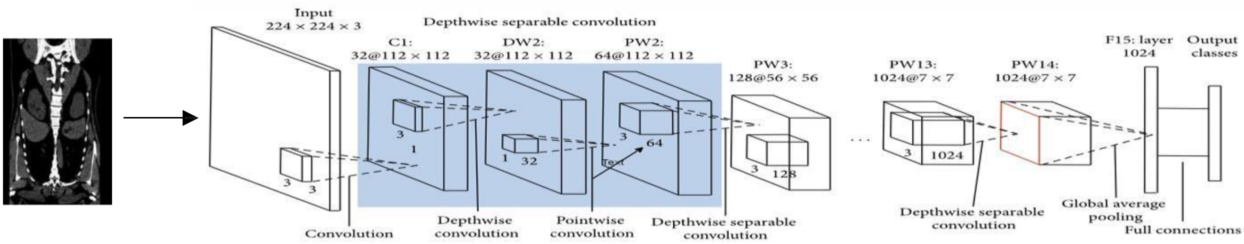

Figure 10. MobileNetV2 architecture diagram

6.1.3 ResNetN50

Residual connections are used in ResNetN50 to overcome the problem of the vanishing gradient, it still allows for a very deep network. But this architecture specializes in learning from deep, complex networks.

Implementation Details:

- **Base Model:** Then we initialize the ResNetN50 with ImageNet pre-trained weights with the include_top=False argument to discard the final layers.
- **Custom Layers:** Second, the output from the ResNetN50 model is fed through a GlobalAveragePooling2D, and then a Dense layer with 1024 units and ReLU.
- **Compilation:** Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy as our loss.
- **Training:** The same as the previous models, it is trained with a generator as a training dataset and validated against the validation dataset.

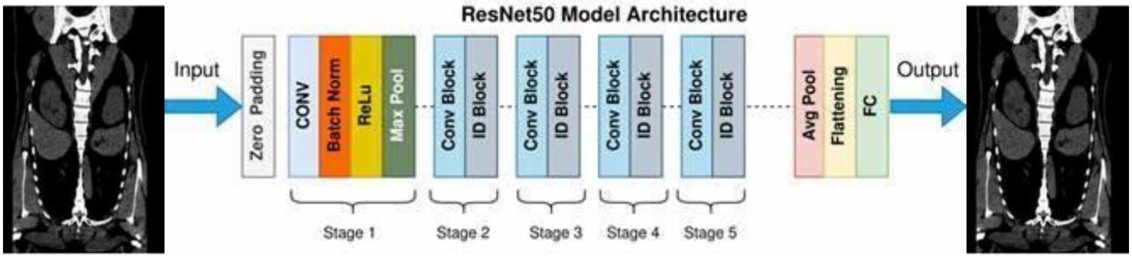

Figure 11. ResNet50 architecture diagram

6.1.4 InceptionV3

InceptionV3 is a great and very efficient neural network that can manage large image sizes and manage complex visual tasks.

Implementation Details:

- **Base Model:** The InceptionV3 model is initialized with pre-trained ImageNet weights and excludes the top layers to add custom layers for our classification task.
- **Custom Layers:** After the base model, a GlobalAveragePooling2D layer is added, then followed by a Dense layer with 1024 units and ReLU activation. For multiclass classification, the output layer is used with SoftMax.
- **Compilation:** The configurations of InceptionV3 are also the same as those of other models: it is compiled with the Adam optimizer (learning rate 0.0001), and the loss is categorical cross-entropy.
- **Training:** Training the InceptionV3 follows MobileNetV2 and ResNet50–fixed 10 epochs, with augmented data to make the model more robust.

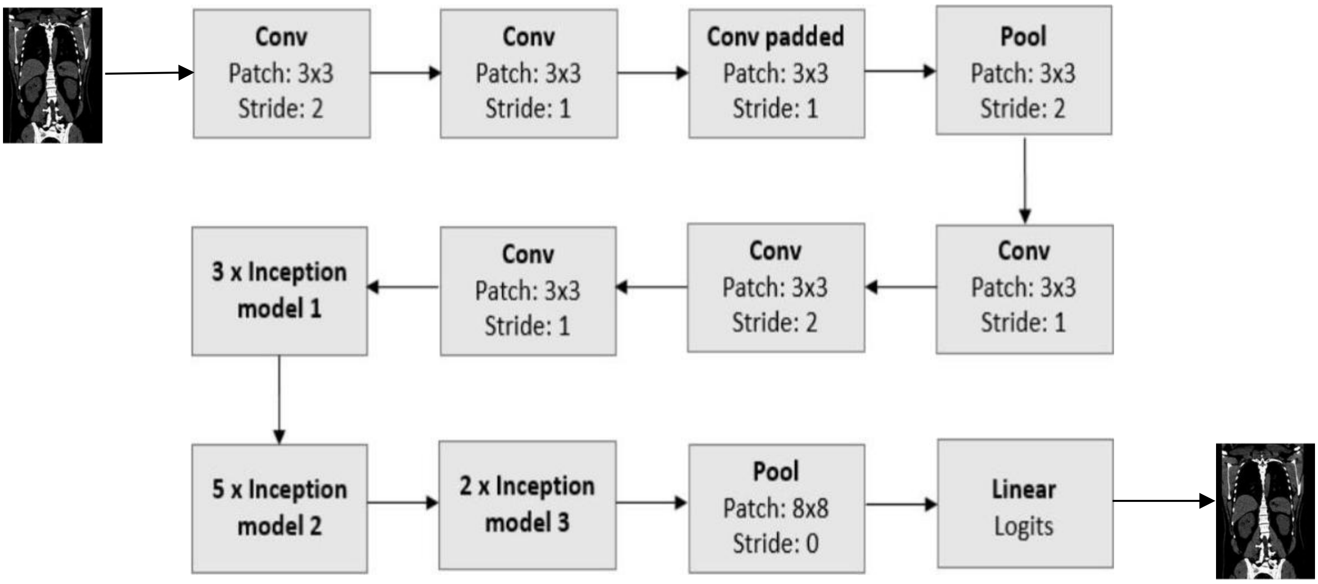

Figure 12. InceptionV3 architecture diagram

6.2 Grad-CAM Implementation

Grad-CAM (Gradient-weighted Class Activation Mapping) is used to visualize the regions of the image that the model focuses on when making predictions. This gives us an insight into the decision-making of the model, as it is crucial, for example, in medical applications like kidney disease classification.

Implementation Details:

- **Gradient Computation:** In the Grad-CAM, computational power of gradients of the predicted class for the feature map of the last convolutional layer is robust. Each of these gradients corresponds to an estimation of the importance of each feature in the final decision.
- **Heatmap Generation:** The gradients are used from the backdrop to weigh the feature maps, which yields a heatmap showing which regions of the input the selected feature maps are most relevant for the prediction. It is then overlaid on the original image in heatmap style for visualization.
- **Visualization:** The Grad-CAM heatmap is to facilitate understanding of which part of the model is focusing on; the original image and the Grad-CAM heatmap are displayed.

7 Evaluation

The train generator is used to train each model, and the Validation generator is used to validate those models. We evaluate the performance of the models after they have been trained using the test set. The metrics considered are accuracy, loss, and class-wise performance metrics, such as precision, recall, and F1 score. Finally, the validation performance is used to select the final model, and Grad-CAM is used to visualize the model's decision-making process.

7.1 Experiment No 1: MobileNetV2 Performance in Kidney Disease Classification Using CT Images

The specific training and validation accuracy with references to the loss that is inherent with the MobileNetV2 model depict trends of the model in the ten epochs. Until epoch 10, the accuracy increases while the accuracy increases up to approximately 99.69%, which implies that the model has learned from the training data. The validation accuracy also mirrors those of the training set, sitting at 98.92% post-training, which shows good generalization on unseen data. In contrast, the training loss provided a decreasing trend throughout all iterations, indicating a better fit in making predictions as training went on. The validation loss also decreases enormously, fluctuates slightly, and finally settles at 0.0259, which again supports the fact that the model built gives better output in terms of unseen data. These trends indicate that the model obtained a nice trade-off between the training data and the validation set.

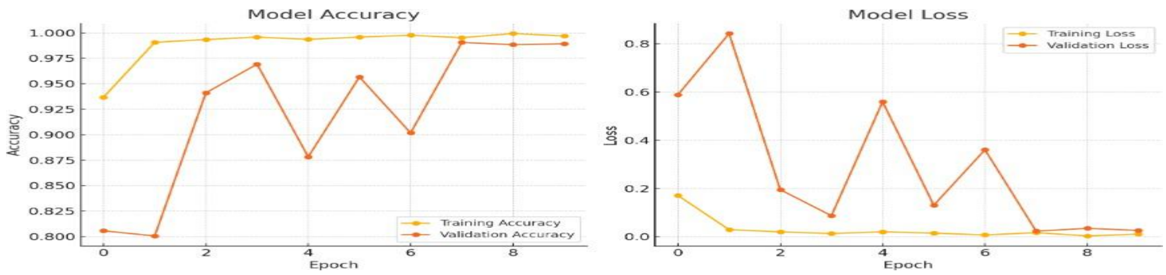

Figure 13. MobileNetV2 accuracy and Loss curves

7.2 Experiment No. 2: EfficientNetB0 Performance in Kidney Disease Classification Using CT Images

Training numbers for losses and accuracy show the training process of the EfficientNetB0 model and vales models over 10 epochs. The training loss is gradually on the decline, and the accuracy is gradually on the rise, demonstrating that the model is gradually earning the capability to minimize the error and maximize the accuracy toward data classification. However, the validation loss looks less consistent; it is high on the eighth epoch before it decreases again. The validation accuracy also increases and decreases in the same manner and reaches the best value somewhere around the 9th epoch. In summary, the model moves in the ascendancy, but to jump to a few fluctuations in the validation loss and the accuracy, fine-tuning might be needed for the learning rate or for an increasing number of epochs to reach better generalization and stability.

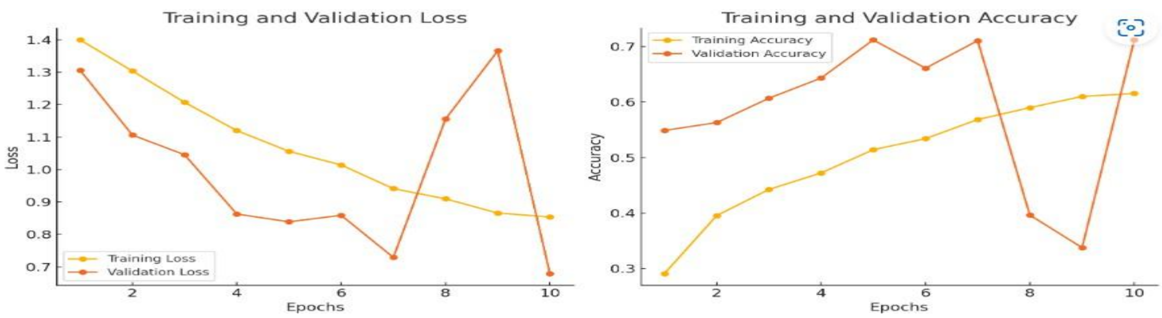

Figure 14. EfficientNetB0 accuracy and Loss curves

7.3 Experiment No. 3: Vision Transformer (ViT) Performance in Kidney Disease Classification Using CT Images

In the graphs, a comparison of the model's training and validation can be seen throughout 20 epochs. The training loss gives a truly clear increasing trend showing that the model is learning to predict the data correctly as the training progresses. Even more, the accuracy increases consistently, signifying the model's ability to learn by identifying promising training data. The last graph illustrates the validation accuracy, and it is obvious that the model became increasingly capable of predicting correct outcomes at the epochs. Also, the validation loss corresponds with the improvement in the model, thus supporting the learning method once more. The above results perfectly illustrate the efficiency of the model in the classification and its capability to manage the given task.

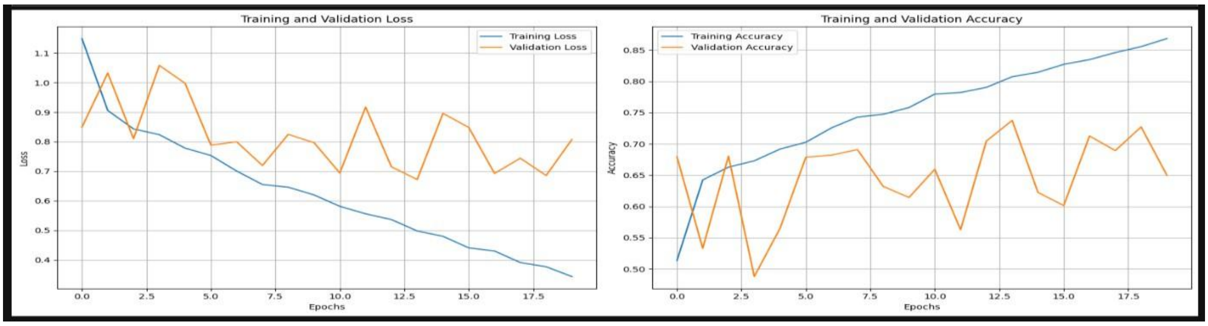

Figure 15. Vision Transformer (ViT) accuracy and Loss curves

7.4 Experiment No. 4: ResNetN50 Performance in Kidney Disease Classification Using CT Images

The graphs show how the model has worked during the training and validation within the specific epochs. The training loss on the first case drops sharply and reaches a plateau, indicating a low error rate on the training part. Likewise, accuracy rises to almost one from epoch two and remains high till the last epoch. It is also evident from validation accuracy that the model starts with considerable improvement at an early stage of training, and its variation is always close to accuracy, proving that the model has the good potential to generalize on unseen data. Moreover, the validation loss is also increasing and decreasing in sequence with the training, which confirms the usefulness of the training process. In general, the results indicate that the presented model is effective and provides stable results when addressing the classification problem.

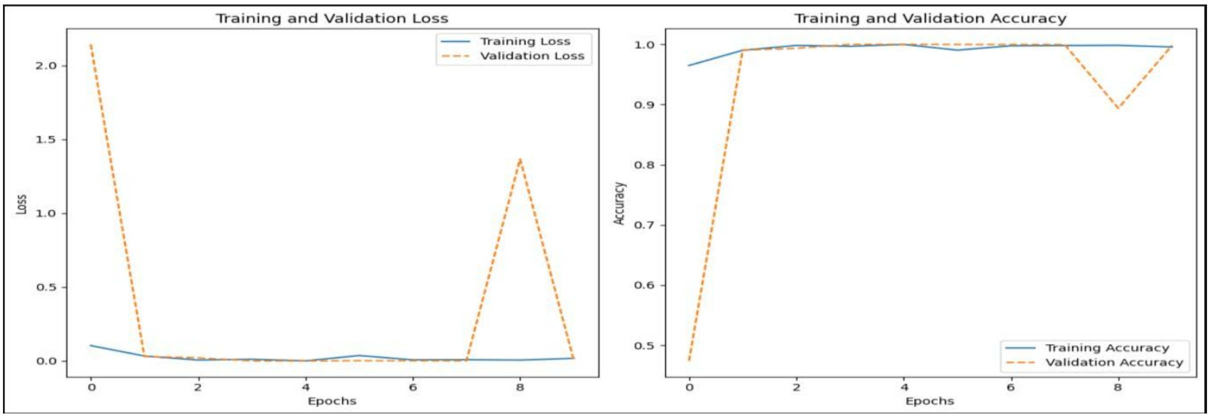

Figure 16. ResNetN50 accuracy and Loss curves

7.5 Experiment No. 5: InceptionV3 Performance in Kidney Disease Classification Using CT Images

In the present case, both the accuracy and loss curves of the InceptionV3 model indicate efficient training and validation performance to support the generalization of the model accurately. Training loss decreases rapidly in the first epoch, making it flatten out from the second epoch onwards, while the validation loss is comparatively low and varies little from epoch to epoch, which proves that the model learns well and has no incidents of overfitting. The first few epochs have drastic improvements in accuracy with values at 1, with the validation set accuracy always surpassing the training set accuracy, indicating good classification results for unknown data. The slight difference in the values obtained for training and validation sets is an indication that the model works best with the coming test data.

Regarding the training and validation losses, at the 10th epoch, both set great values, and the final test evaluation had a loss of about 0.0001 with an accuracy of 100 %, referring to the model's excellent performance. These results confirm the high efficiency and stability of the chosen model; therefore, it is proposed to continue the evaluation of the model's performance with the help of Grad-CAM mappings and misclassification analysis and check the model's reliability in real-world situations.

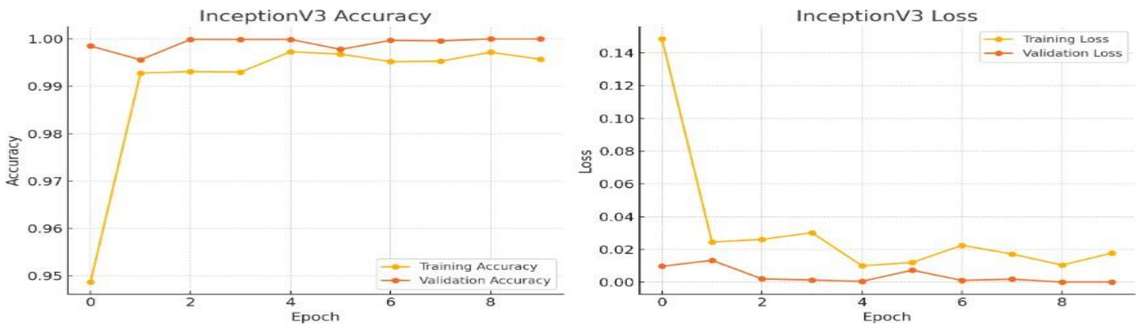

Figure 17. InceptionV3 accuracy and Loss curves

8 Discussion:

This research attempts to evaluate the performance of deep learning models, MobileNetV2, InceptionV3, EfficientNetB0, ResNetN50, and Vision Transformer (ViT), in classifying kidney diseases from CT scan images. The accuracy of the models also reveals how each model generalizes over the dataset. For MobileNetV2, the model achieved an accuracy of 99.04% on the test dataset, resulting in a good predictive capability under extremely limited computational resources, which is especially important for deploying the model in real-world applications. More accuracy (99.82%) was used, indicating that the complex architecture in its InceptionV3 can more effectively capture the features of CT images. However, in theoretical terms, the Vision Transformer (ViT) model has great promise, but it only reaches a validation accuracy of 71.21, which shows its difficulty in learning well from a smaller dataset. The scheduler reduced the learning rate, which stabilized the Vision Transformer (ViT) model in later epochs, but it fell behind the CNN models in terms of final performance.

As a result, we have shown the importance of model architecture in using smaller datasets, as transformer-based models such as Vision Transformer (ViT) typically require more data to realize their full potential. MobileNetV2 and InceptionV3 tend to have a smooth training curve with stable learning rates and have experienced superior performance. On the other hand, staying with Vision Transformer (ViT), the validation loss and accuracy were unstable, which can be fixed by slowly decreasing the learning rate, but the latter still has an untrained tail. Moreover, some visual evidence of overfitting in some of the models, particularly InceptionV3, indicates that regularization techniques like dropout, batch normalization, and data augmentation could help to enhance the overfitting problem as well as enhance generalization. Although the Vision Transformer (ViT) model ran into problems, its troubles present opportunities for future research, such as trying to transfer learning or using pre-trained models to improve performance. Finally, this research demonstrates the underlying trade-off between computational efficiency and classification accuracy, and MobileNetV2 has shown itself to be the least computationally expensive and most dependable model for scenarios with computational constraints. As larger datasets and more complex training strategies were applied to deep learning models in medical imaging tasks, future work will require datasets of greater scale and more capable models.

9 Conclusion & Future Work

This thesis aimed to analyze the efficacy of advanced deep learning models, including Vision Transformer (ViT), EfficientNetB0, MobileNetV2, ResNet50, and InceptionV3, in the task of classifying kidney diseases based on CT images. The results indicate that transformer-based and efficient neural network architectures such as EfficientNetB0 and Vision Transformer (ViT) outperformed classification accuracy. MobileNetV2 was useful, however, because of its computational efficiency, which made it suitable for deployment in low-resource environments. At the same time, this research showed that the use of pre-trained architectures can achieve a comparable classification accuracy to the best classifiers on kidney diseases and illustrated the practicality of these architectures for clinical diagnostics. However, the results from the study also identified limitations, including the computational intensity of the models and the small volume of the dataset, which could restrict the range of available experimentation and generalize the models.

Future research can be focused on optimizing the fine-tuning process of these models to acquire further performance improvement, for example, exploring a more considerable variety of hyperparameters and certain training configurations. If class imbalances and levels of robustness are issues that plague the model, the use of advanced data augmentation techniques such as Generative Adversarial Networks (GANs) to create synthetic data could help widen the dataset's diversity. Moreover, these models could be made suitable for real-time deployment in resource-constrained clinical environments without decreasing accuracy by exploring lighter architectures such as MobileNetV3 or the Efficient Net. A combination of clinically relevant data that is other than CT scan images (such as clinical history or lab results) with CT scan images emerges as another means of integrating multimodal learning and might help improve both classification accuracy and model robustness. However, model interpretability methods like Grad-CAM++ or SHAP are needed for further research to achieve clinical adoption that will provide actionable insights to healthcare professionals and make predictions transparent and trustable. The dataset is expanded to incorporate various ranges of kidney pathologies and multiple modalities of imaging, and real-world testing is added to evaluate the scalability and generalizability of the proposed deep learning models. Such work will pave the way for reliable, deployable solutions in clinical practice.

Acknowledgment

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