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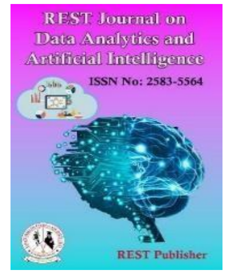

Fine-Tuning CNN Models for Accurate Kidney Condition Classification from CT scans

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Abstract: *Classifying kidney conditions is a critical task in clinical imaging, with huge implications for affected person management, prognosis, and remedy. Using CT test photographs, this observe makes use of Convolutional Neural Networks (CNNs) to correctly classify different kidney conditions, together with kidney tumors, stones, regular kidneys, and cysts. Our method demonstrates the capacity of advanced deep gaining knowledge of strategies to improve diagnostic performance and accuracy in medical settings, notwithstanding the complexity of decoding scientific imaging data. We optimized a number of cutting-edge CNN architectures, inclusive of ResNet18, MobileNetV2, and EfficientNet, to take advantage in their distinct advantages in picture category and function extraction. Our effects show that in spite of the noise and variability of CT scans, the model performs robustly in numerous kidney conditions, has suitable accuracy and reliability Confusion matrix evaluation improves model performance evaluation with the aid of imparting information at the inequitable distribution and distribution of resources. The consequences verify the application of our take a look at and show the capacity of CNN as a dependable diagnostic tool within the context of epilepsy. The have a look at highlights the importance of automated procedures for faster and extra accurate prognosis of kidney condition and, in the long run, improved patient results.*

Keywords: *Kidney Condition Classification, Convolutional Neural Networks, Medical Imaging, CT Scans, Deep Learning.*

1. INTRODUCTION

Recent advances in machine learning and medical imaging are providing new opportunities for automated diagnosis of many conditions. Kidney conditions, such as cysts, stones, and tumor, pose a significant obstacle to appropriate treat ment and accurate diagnosis. Accurate and timely diagno sis improves patient outcomes and facilitates treatment. CT (Computed tomography) images are widely applied in medical field practices. Analyzing such images with the assistance of artificial intelligence, specifically CNNs, might be a promising approach to achieving the intended task of nephrology classi fication. The reason convolutional neural networks learn hierarchical features is that they perform exceptionally well in identifi cation and classification tasks in images. Researchers have shown that CNN architectures such as ResNet, MobileNet, and EfficientNet could possibly yield top-of-the-line perfor mance in various problems involving the classification of images, including medical diagnosis. For example, the residual learning framework of ResNet, which is well known, was successfully applied to medical imaging and improves clas sification accuracy of a variety of disorders such as renal ailments [1]. An effective detection without affecting the speed makes MobileNetV2 very profitable for resource-constrained environments because of a simplified architecture and low computational cost [2]. In addition, EfficientNet can deal with complicated tasks in medical imaging due to its scalability as well as enhanced parameter efficiency that enhances its diagnostic skills even more in a clinical scenario [3]. In this paper, we are using labeled CT scan data to fine-tune CNN architectures toward the diagnosis of kidney conditions. Models must be trained and optimized with an angle that dis tinguishes such renal cancers, stones, cysts, and healthy renal conditions. The models will determine the efficacy and adapt ability of clinical decision-making and patient management. There have been many papers published recently showing the integration of healthcare with deep learning may actually improve the diagnostic accuracy and minimize the workload for radiologists [4,5]. The outcome of this project will be to contribute to the continuous effort by providing practitioners with a powerful tool in the aid of their diagnostic processes and enabling prompt intervention for patients suffering from kidney-related disorders.

2. LITERATURE SURVEY

Deep learning, in the form of convolutional neural net works (CNNs), has allowed the medical analysis of images to undergo a sea change. Using CNNs, scientists are now able to solve sophisticated problems of classification that are based on a large spectrum of conditions. Nephrologists have to, therefore, correctly categorize different conditions arising in the kidneys - a combination of tumors, stones, cysts, and normal variations-for timely diagnosis and treatment. Several studies have demonstrated how well CNNs classify kidney problems using CT scans and other imaging modalities. For instance, Khan et al. (2020) proved that CNNs can improve the diagnostics of imaging, especially with urological conditions, by classifying kidney-related conditions with high accuracy [6]. A very popular architecture for problems in medical imag ing is residual networks or ResNets. This deep learning archi tecture incorporates skip connections and, therefore, enhances efficiency in learning by lessening the vanishing gradient problem that arises in very deep networks. ResNet was demon strated to be capable of performing better on image classifica tion tasks, including healthcare-related ones, than other earlier CNN designs [7]. According to He et al. (2016). For instance, experiments with the application of ResNet for kidney imaging demonstrated high accuracy in the discrimination between the conditions of kidneys. Such success was demonstrated, for example, by Ghafoorian et al. (2017) and Gole et al. (2020), who applied ResNet for the classification of renal tumors from datasets for imaging [8][9]. Another variant of CNN is MobileNetV2, which has sig nificantly enhanced image classification, especially when pro cessing power is limited. This allows it to run and classify on the move on mobile without compromising on precision due to its lightweight architecture. MobileNetV2 is an architecture introduced by Sandler et al. (2018) that applies depth-wise separable convolutions such that the model could have reduced complexity without trading in quality or medical images for classification [10]. This helps with real-time diagnosis in healthcare scenarios as it can do quick inference. This is compound scaling: a new technique developed by Tan and Le (2019) that optimizes depth, width, and resolution with methodical model scaling for maximizing performance while minimizing the costs of computations [11]. Their work shows that Efficient Net can outperform existing architectures such as Reset and Dense Net on several image recognition benchmarks, meaning that the potential for this architecture might be useful in medical applications especially for classification on kidney condition [12]. An interesting number of studies has been focused on applying deep learning techniques in particular with regard to the differentiation between tumors, stones, and normal kidney tissues in the classification of kidney conditions. A very notable endeavor in 2018 was carried out by Ghafoorian et al., where renal masses were classified from CT images using deep learning models. The promising results include that CNNs can identify subtle imaging features important for diagnosis [13]. Furthermore, a systematic review of deep learning applications in urology by Yi et al. (2020) summarized the ongoing advancements and emphasized the role of CNNs in improving diagnostic accuracy and predictive modeling for patients suffering from urinary tract conditions [14]. Furthermore, in 2021, Raza et al. published a meta-analysis which demonstrated the CNN-based techniques may boost up the detection rate for various kinds of kidney conditions. This not only allows higher accuracy but more importantly, helps radiologists in making clinical decisions with the second opinion [15]. All these outcomes make a strong case for CNN architectures in medical imaging, especially in the very challenging field of kidney condition categorization; they indicate how they may support earlier and more accurate diagnoses.

3. METHODOLOGY

Dataset Description: The CT Kidney Dataset is the dataset of this project, which consists of a complete set of images of kidney obtained through frontal, lateral, and focal views. It has been obtained from the Picture Archiving and Communication System of various hospitals located in Dhaka, Bangladesh. The patients of this dataset are diverse kidney conditions and range from a normal case, cyst, stone, and tumor case, etc. The dataset focuses on the abdomen and urogram using both coronal and axial cuts gotten from both contrast and non-contrast studies. Sensitive DICOM images were selected and then all images exported as a lossless JPG, with privacy-protected patient data and metadata completely removed. One radiologist, along with a medical technologist, closely observed and verified the accuracy and clinical relevance of each image. There are 12,446 distinct images containing in the database, grouped into the 4 condition as following: 5,077 normal conditions, 3,709 cysts, 1,377 stone-related abnormalities, and 2,283 malignan cies. This very high-power, multi-dimensional database is an excellent tool for developing automated diagnostic models. This is further achieved in furthering the diagnosis of kidney conditions by making a critical contribution to the recent article "Vision transformer and explainable transfer learning models for auto detection of kidney cyst, stone, and tumor from CT-radiography," published in Scientific Reports 2022.

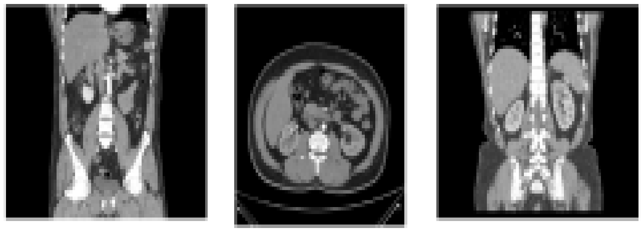

FIGURE 1. Kidney CT Scan Image Dataset [16]

Data Processing: 1) Data Preprocessing: The images are categorized within a directory by category. Under this, each category is labeled with its specific directory, i.e. Cyst, Normal, Stone and Tumor. Many transformations have been executed on the input data to ensure ready condition for training such as resizing each image to a 224 by 224 size, horizontal flips with randomness as well as normalization of the data using the mean value. supplied for the ImageNet dataset and the standard devia tion. Those transformed images are loaded through torchvi sion.datasets.ImageFolder. 2) Data Splitting: An 80-20 splitting is done for the same dataset, which splits it into training and testing datasets. Though the training set is used in the updation of model parameters regarding weights in the output layer, the testing dataset is used to judge the performance of the model at the conclusion. 3) Data Loading: PyTorch's DataLoader is used to do batch loading for the training as well as validation datasets. For ensuring that the data are properly randomised across every epoch, a batch size of 32 is selected, and the training set is shuffled.

Block Diagram

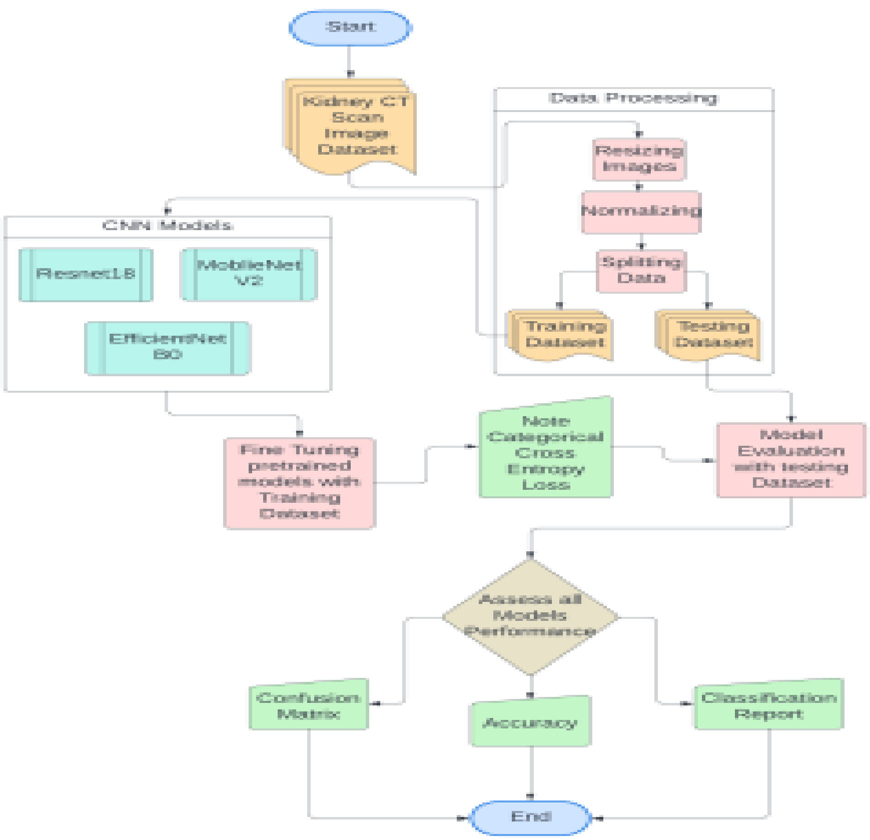

FIGURE 2. Flow Chart

CNN Models: Based on CT scan pictures, this study uses several Convolutional Neural Network (CNN) architectures to classify kidney conditions, specifically Cyst, Normal, Stone, and Tu mor. We intend to use the feature extraction and classification strengths of popular pre-trained models, namely ResNet18, MobileNetV2, and Efficient Net. Transfer learning is used to optimize the three model's performance, with a focus on kidney condition categorization.

1) ResNet: ResNet18 is a member of the ResNet family which utilized residual connections to solve the vanishing gradient problem associated with very deep networks. These connections enable the network to learn identity mappings between layers, thus easing the training of very deep architectures.

• **Architecture Overview:** The two convolutional layers and identity connections, which add the output from one layer to another directly, constitute the 18 layers of ResNet18. There are two convolutional layers in each basic block, which include mapping along the output. This architecture permits effectively training deeper networks without a speed sacrifice by improving gradient flow during backpropagation.

• **Modifications for Kidney Classification:** In this, a 4-class output layer was replaced for the final fully connected layer of ResNet18. Only the last few layers of the network were trained on the dataset of kidney CT scans; the earlier layers-the ones pre-trained on ImageNet-were frozen.

2) MobileNetV2: MobileNetV2 is another lightweight ar chitecture of CNN that has been proposed particularly for em bedded and mobile applications. It is simplified with reduced computational complexity using inverted residual connections and depthwise separable convolutions.

• **Architecture Overview:** The depth wise separable con volutions hence reduce the number of parameters and computations, basically by decoupling the procedures for convolution. The improvement in the architecture with regard to speed and efficiency is further enhanced through connecting thinner bottleneck layers by shortcut connections made in inverted residual blocks.

• **Modifications for Kidney Classification:** The fully connected layer of the pre-trained MobileNetV2 model, originally designed to provide 1,000 classes, was modified to produce a 4-class output layer compliant with our classification goal. Although fine-tuning the final few layers for optimal exploitation of the features learned in ImageNet, we froze the first few layers.

3) Efficient Net: Simultaneously scaling depth, width, and resolution of input images: The new CNN design in Efficient Net incorporates compound scaling to enhance the model accuracy-performance tradeoff.

• **Architecture Overview:** While its compound scaling strategy is much different from the previous designs, Effi cientNet manages to reach state-of-the-art performance using fewer parameters. There exist model family variants

which provide scalable capacity as well as a substantial range of performance, ranging from EfficientNet-B0 to EfficientNet-B7.

• **Modifications for Kidney Classification:** For the current task, the efficient base variation with fewer numbers of parameters was chosen, which is EfficientNet-B0. A 4- class output layer designed for condition categorization was employed instead of the last fully connected layer, and the last layers were tuned.

Model Evaluation

To validate the models after the training process, a held out test set is used and classification performance is tested to assess what the model can do. Accuracy is the most common evaluation criterion to represent the percentage of properly predicted instances regarding all the instances of the test set. Precision measures how well the model reduces false positives by determining the ratio of true positives to the sum of true positives and false positives. Recall, which is defined as true positives divided by the sum of false negatives and true positives, suggests the degree to which the model is able to classify all relevant instances correctly. The harmonic mean of precision and recall comprises the F1-score, which gives a balanced view over the overall quality of the model.

4. RESULTS AND DISCUSSION

This section assesses the performance of three models for kidney condition classification from CT scan images: ResNet18, MobileNetV2, and EfficientNetB0. The report for each model consists of classification reports, confusion matri ces, and training performance.

A. Model's Performance

1) Categorical Cross-Entropy Loss: For multi-class clas sification problems, categorical cross-entropy loss was used across all models. For all models, the train loss was decreasing, reflecting the models' improvement in terms of their discrim ination capability as they learned more about the data.

• ResNet18: it essentially reduces the error steadily and shows a training loss of 0.0114 by Epoch 10.

• MobileNetV2: Performs better in the task of minimizing errors, where it attained the smallest train loss in Epoch 10 as 0.0187.

• EfficientNetB0: It showed a mid-range error reduction with the training loss at 0.1397 in Epoch 10.

2) Accuracy: The ultimate training accuracy of the models illustrates their ability to categorize among the varied cate gories of kidney diseases:

• ResNet18: Training accuracy was 99.60%.

• MobileNetV2: 99.62% is the greatest training accuracy, thanks to MobileNetV2.

• EfficientNetB0: Achieved 98.67% of the training accu racy with EfficientNetB0.

For accuracy, MobileNetV2 tops the list with EfficientNetB0 very close in terms of accuracy while for ResNet18 the accuracy is a little low. However, to get a proper understanding of the generalization capability of the models, the models need to be tested on unseen data.

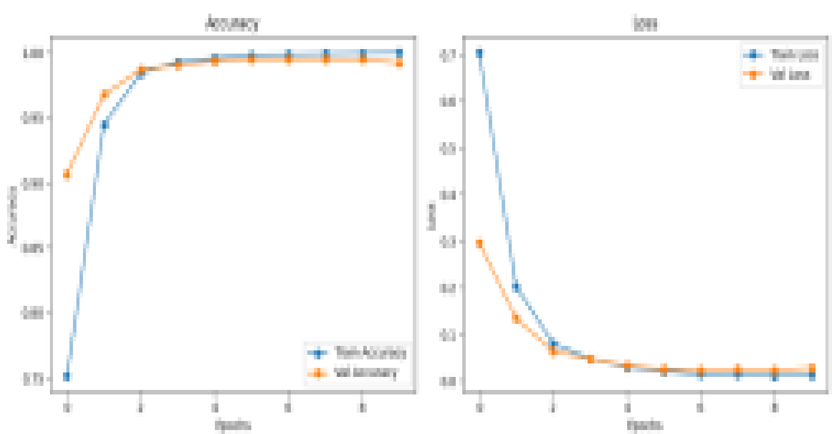

FIGURE 3. ResNet18 Model Performance

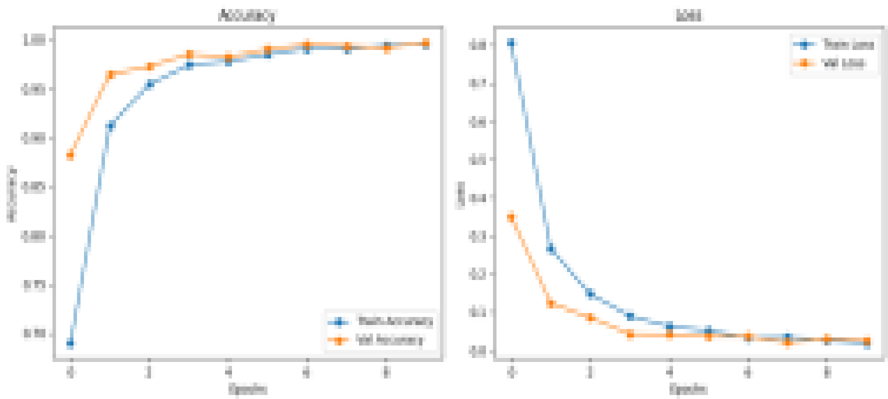

FIGURE 4. MobileNetV2 Model Performance

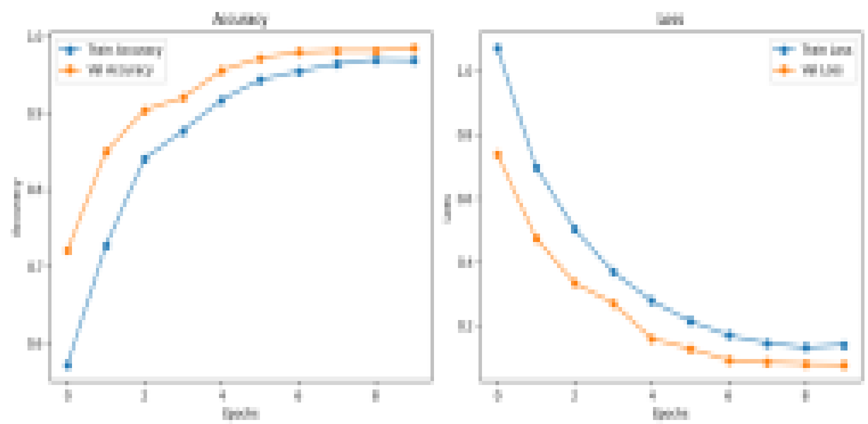

FIGURE 5. EfficientNetB0 Model Performance

Confusion Matrix: The confusion matrices essentially represent the four kid ney conditions (tumor, stone, cyst, and normal) and give an extensive view into the performance of each model in terms of classification:

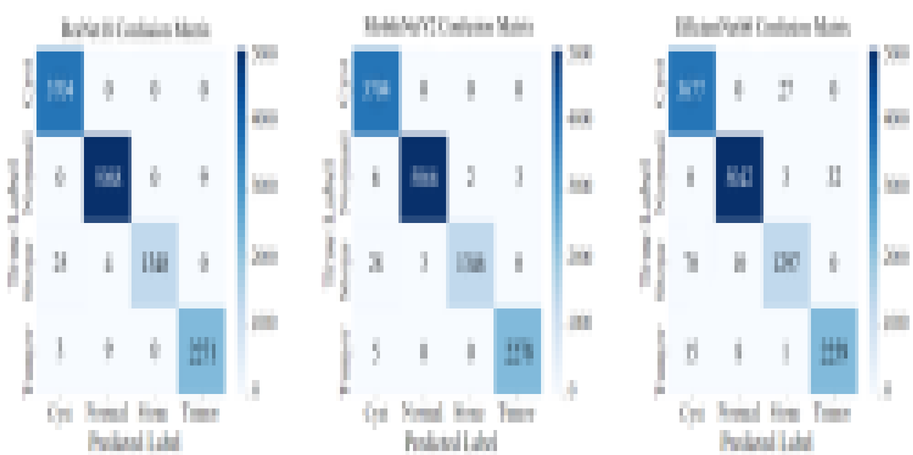

FIGURE 6. All Model's Confusion Matrix

It is then by the confusion matrix, showing that the model was working appropriately under all conditions with extremely few errors.

Classification Report

The classification report shows accuracy, macro averages and weighted averages in addition to precision, recall and F1- score for each class:

• Precision: On all classes, the model had impressive precision; in particular, it achieved a perfect scores for ”Normal” and ”Tumor,” which reflected the fact that the predictions were quite reliable.

• Recall: The model had perfect recall of all the true positives as indicated by superb recall of ”Cyst” and ”Tumor” at 1.00. ”Stone,” though had slightly poorer recall of 0.97, suggesting more occurrences could have been captured.

• F1-Score: All classes of efficacy are good. F1 scores are those based on the balance between recall and precision. The model performed well in the ”Normal” and ”Tumor” classes with a score but failed to perform well on the ”Stone” class.

TABLE 1. Evaluation Results For Different Models

Model	Class	Metrics		
		Precision	Recall	F1-Score
MobileNet	Cyst	0.99	1	0.99
	Normal	1	1	1
	Stone	1	0.98	0.99
	Tumor	1	1	1
	Accuracy	1		
	Macro avg	1	0.99	0.99
	Weighted avg	1	1	1
ResNet18	Cyst	0.99	1	1
	Normal	1	1	1
	Stone	1	0.98	0.99
	Tumor	1	1	1
	Accuracy	1		
	Macro avg	1	0.99	0.99
	Weighted avg	1	1	1
EfficientNet	Cyst	0.98	0.99	0.98
	Normal	1	0.99	0.99
	Stone	0.98	0.94	0.96
	Tumor	0.99	0.99	0.99
	Accuracy	0.99		
	Macro avg	0.98	0.98	0.98
	Weighted avg	0.99	0.99	0.99

All things considered, the model performs admirably when it comes to kidney condition classification, showing high accuracy, precision, recall, and low categorical cross-entropy loss. This hints that the model might actually be useful in the clinical domain, with perhaps a few more improvements for the” Stone” classification.

5. CONCLUSION

The three CNN-based classification models of renal condi tion developed using ResNet18, MobileNetV2, and Efficient NetB0 have been tested at length and it can be seen that these models are capable and promising for clinical use where high precision in diagnosis is demanded. The models showed strong learning abilities as MobileNet2 achieved the highest training accuracy at 99.62% with the lowest categorical cross-entropy loss at 0.0187. The rest two were ResNet18 and Efficient NetB0. Further capability is demonstrated in the confusion matrices and classification reports, in which scenarios such as ”Cyst” and ”Tumor with fewer misclassification cases can be more proficiently classified using MobileNetV2. ResNet18 and EfficientNetB0 performed relatively quite well but still have plenty of room to move forward, especially for ”Stone” scenarios. Such models, the findings go on to assert, are very promising towards automating the process of classifying kidney conditions, thus improving speed and accuracy within health care in diagnostic procedures.

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