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MobileNetV2-Based Deep Learning Model for Efficient Classification of Kidney Disorders

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Abstract: Kidney stone also known as renal calculi, is a painful urological condition which can lead to serious complications if not detected timely. In the present times, there has been a surge in the number of kidney stone patients. Conventional approaches have several drawbacks in detection of kidney diseases including delays, incorrect predictions and a lot of manual effort. Deep Learning (DL) based algorithms have overcome these limitations and offered a promising solution called Convolution Neural Networks (CNN) which is excellent in capturing the complex image patterns. CNNs have transformed the task of medical imaging by enabling more accurate and efficient predictions. In this study kidney image classification is done using MobileNetV2, a lightweight, pretrained CNN architecture and the images are categorized into four classes that are cyst, stone, tumor and normal. The model demonstrated excellent outcomes by achieving an accuracy of 96 %, recall of 95% and precision of 96%. The results of this study proves the capability of CNNs in clinical tasks for enhancing patient care.

Keywords: Deep Learning, Convolutional Neural Networks, Kidney Stone

I. INTRODUCTION

Kidney is an important organ of human body that helps to maintain the balance of body by carrying out essential functions such as filtering blood, regulating blood pressure and removing waste. Kidney stones are formed due to the accumulation of solid crystals of minerals and salts in kidneys which can cause extreme back pain and infections in the urinary tract [1].

Early detection of kidney stones is crucial to avoid irreparable damage and effective treatment [2]. Existing techniques for kidney disease identification includes Computed Tomography scans, ultrasounds and X-Rays [3]. But these traditional methods are time consuming and subject to errors [4].

DL models specifically CNNs have emerged as a breakthrough in medical sector for classification of kidney stones in the recent times [5]. CNNs are a special type of neural networks which are excellent in feature extraction and image categorization [6]. This study shows the potential of a pretrained CNN model called MobileNetV2 in precise identification of kidney problems which can help healthcare professionals in providing timely treatment of patients, resulting in improved patient outcomes.

Further sections contain the following: Section 2 is Literature Review, Section 3 is Materials and Methods, Section 4 is Proposed methodology, Section 5 is Results and discussion and Section 6 finally contains the conclusion and future scope of this study.

II. LITERATURE REVIEW

This section describes the existing work in the field of kidney stone detection.

Table 1. Related Study done in this field

Reference No	Methodology Used	Objective	Limitation
1	Proposed a hybrid model combining CNN and SVMs to enhance the detection accuracy. To handle class imbalance, SMOTE was used and 5-fold cross validation was applied to avoid overfitting.	To enhance the robustness of kidney diagnostics systems with the use of advance hybrid models.	High computation cost, inability of SVMs to handle complex image patterns.
2	Histogram Equalization, Embossing, Watershed based segmentation were used for preprocessing. CNN-Relm model was employed to train and test the kidney CT images.	To increase the accuracy of kidney stone segmentation compared to CNN and ELM models.	No specification about the dataset used.

3	Capsule Networks was created utilizing dynamic routing and vector-based capsules to pinpoint the exact location of kidney stones.	To perform the precise localization of kidney stones while preserving spatial coherence.	Limited dataset was used.
4	Mask-RCNN was used along with ResNet-50 and ResNet-101 to correctly identify kidney stones. Dataset contained 15000 images of kidney, uterus and bladder. Model achieved an overall precision of 91%.	To design an automatic approach for rapid and enhanced kidney stone detection.	The model only predicted the presence or absence of kidney stones. It did not focus on different kidney diseases.
5	Proposed ensemble DL approach involving finetuning VGG-16 model by refining the last 20 layers of it for obtaining high level, task-specific features. Attenuation training was applied to improve the learning process.	To overcome the limitation of single baseline models in categorization of multiple similar classes.	High computation cost.
6	Combined the YOLOV10 model with channel attention mechanism. Model achieved an impressive accuracy of 93.7%.	To increase the model's ability to focus more on the critical areas in medical images.	Slower inference, poor performance on imbalance dataset.
7	Ensemble model comprising of DarkNet19, InceptionV3, ResNet101, DenseNet169, MobileNetV2, VGG16, GoogleNet, AlexNet, ShuffleNet, SqueezeNet, DNN, and Xception were applied for classification. For detection a combination of YOLO v5x6, YOLO v5s6, YOLO v8n, YOLO v9n were employed. Feature selection was performed using techniques like ReliefF, KNN and K-Fold validation. A flask based user-friendly interface was developed for medical experts.	To develop a DL-based system for reliable diagnosis of kidney problems.	No information is given about the size and source of the dataset used.
8	Blur, MedianBlur, ToGray, and CLAHE were applied for data augmentation. YOLOV8 model was employed to identify the presence of kidney stones.	To address the limitations of traditional methods in kidney stone detection by using DL models.	Results are not satisfactory. The values of all the evaluation metrics are below 85%.
9	EfficientNet-B7 was used for diagnosis of kidney stones. The model was also compared with other segmentation models such as SegNet, DeepLabV3+, UNETR and Res U-Net but, EfficientNet-B7 achieved higher accuracy than all other models.	To develop a model that can identify different size of kidney stones from CT images.	Limited dataset was used.

10	Firstly, all the collected images were preprocessed then Guided active contour was applied for the segmentation of kidney stones. VGG-16 was used for feature extraction and classification. The model attained a training accuracy of 94%, validation accuracy of 91% and testing accuracy of 90%.	The goal was to create an autonomous system for quick and accurate recognition of kidney stones.	No information is given about the dataset used.
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III. MATERIALS AND METHODS

This section describes the materials and methods used in this study.

A. Dataset

The dataset used in this study is taken from Kaggle(<https://www.kaggle.com/datasets/nazmul0087/ct-kidney-dataset-normal-cyst-tumor-and-stone>). The dataset was collected from PACS (Picture archiving and communication system) from various hospitals in Bangladesh and Dhaka []. The dataset contains total 12446 Kidney images and consists of 4 classes-Normal, Cyst, Stone and Tumor. The distribution of the dataset is shown in Table 2.

Table 2. Distribution of dataset

Class	No of Images
Normal	5077
Cyst	3709
Stone	1377
Tumor	2283

B. Model Used

MobileNetV2: It is a lightweight CNN model particularly made for mobile and embedded vision [7]. It consists of inverted residual blocks, linear bottlenecks and depth wise separable convolutions which makes it better than original MobileNet giving more accuracy and speed along with reduced computation cost.

C. Technique Used

Transfer Learning: It is a technique used in deep learning where knowledge acquired by training usually on a large dataset is utilized as base for another dataset. It uses a pretrained model which has learnt the primitive or low-level features relevant for any image classification tasks. It freezes the initial layers and finetunes the top layers so that model can adapt to new dataset by learning the high-level features specific to the new dataset. It saves the time and effort of finding a large dataset for training and reduces computational cost.

D. Performance Measures

Accuracy: It is the ratio of correctly predicted instances divided by the total predicted instances. Its mathematical formula is given in equation 1.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad [1]$$

TP: It stands for true positive. The instances correctly predicted as positive.

TN: It stands for true negative. The instances correctly predicted as negative.

FP: It stands for false positive. The instances incorrectly predicted as positive.

FN: It stands for false negative. The instances incorrectly predicted as negative.

Precision: It is the ratio of correctly predicted positives divided by total predicted positives.

$$\text{Precision} = \frac{TP}{TP+FP} \quad [2]$$

Recall: It is the ratio of correctly predicted positives divided by total actual positives.

$$\text{Recall} = \frac{TP}{TP+FN} \quad [3]$$

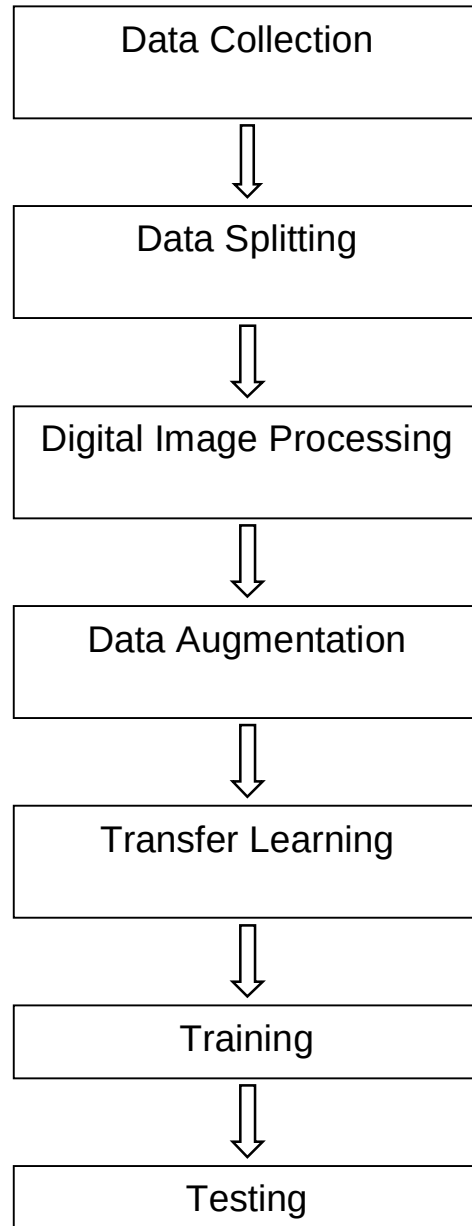
F1-Score: It is the harmonic mean of precision and recall.

$$\text{F1 - Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{(\text{Precision} + \text{Recall})} \quad [4]$$

IV. PROPOSED METHODOLOGY

In this study Kidney Image Classification is performed using a CNN architecture called Mobile NetV2 on an image dataset.

Fig 1. The flowchart representing the methodology used



- 1) After the data collection, the dataset is divided into training, testing and validation sets with percentage 70%, 15% and 15% respectively. The distribution obtained after division is depicted in Table 3.

Table 3. Distribution of dataset after splitting

Class	Training Set	Validation Set	Testing Set
Normal	3553	761	763
Cyst	2596	556	557
Stone	963	206	208
Tumor	1598	342	343

- 2) A function is defined for applying digital image processing on the data to enhance the image quality before giving it to CNN. It firstly applied a Median blur filter for noise reduction. Contrast enhancement is applied using CLAHE, a histogram equalization technique to better differentiate the image classes. Images are normalized and resized to 224*224 which is the required input size of Mobile Net V2. At last, the images are converted from grayscale to RGB as per the need of Mobile Net V2. Then the function is applied on all the three sets that is training, validation and testing.
- 3) Image Data Generator is used to apply data augmentation on training mages to enhance the generalizability of the model. It includes rotation, shifting the images horizontally and vertically, zooming, flipping, shear transformations, changing brightness of the image and normalizing the pixel values. For validation and testing sets only normalization is performed. All the images are resized to 224*224 pixels, and the batch size is taken to be 32.
- 4) Transfer learning is employed using the MobileNetV2 architecture. MobileNetV2 is loaded with the pretrained weights from the ImageNet dataset to save time and resources required for training the model from scratch and providing the hierarchical features useful for general image classification tasks. Original classification layer is removed, and custom classifier is added appropriate for Kidney image classification. The input shape is set to 224*224 pixels with 3 color channels. Initial layers of the model are frozen and only the top 40 layers are trained again so that the model learns the feature relevant for Kidney Image classification. Global Average Pooling is applied for feature extraction and dimensionality reduction to reduce computations followed by a dropout layer is applied with a 50% rate to reduce overfitting and at last a dense layer with SoftMax activation. Adam optimizer is used for smooth and quick convergence.
- 5) The model is trained for 30 epochs along with a set of callback functions. ReduceLROnPlateau reduces the learning rate when model stops improving; EarlyStopping is applied to stop the training when validation loss does not improve for certain number of epochs. Here it is 7 epochs which means if validation loss does not improve for 7 epochs, then training is stopped.

V. RESULTS AND DISCUSSION

Model has achieved a very high training and validation accuracy which means that model has well learnt the relevant features for classification of Kidney images. The precision and recall value are also high and similar suggesting that model has a strong balance in identifying true positives and minimizing false positives. The loss value for both training and validation is low indicates that model has converged without any overfitting.

Table 4. Training and the validation performance of the model.

Set	Accuracy	Precision	Recall	Loss
Training	96.59%	96.78%	96.32%	0.1071
Validation	97.05%	97.15%	96.73%	0.0994

The value of all evaluation metrices for testing set are greater than 95% shows that model has performed very well on unseen data. High accuracy indicates that model has accurately classified majority of the test images. High precision shows that model has hardly miscategorized healthy images as sick. High recall implies that model has rightly identified images with kidney disease. F1 score of 95% conveys that model has a strong balance between precision and recall.

Table 5. Testing performance of the model.

Accuracy	Precision	Recall	F1-Score
96%	96%	95%	95%

Fig2. Graphs showing the comparison of training and validation accuracy for MobileNetV2.

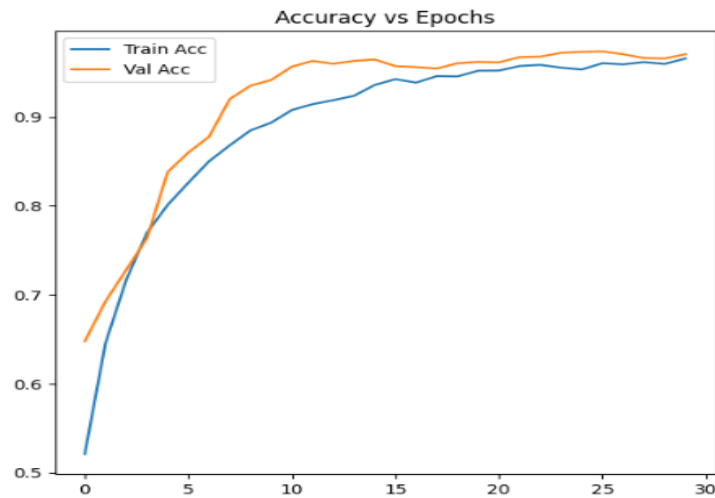
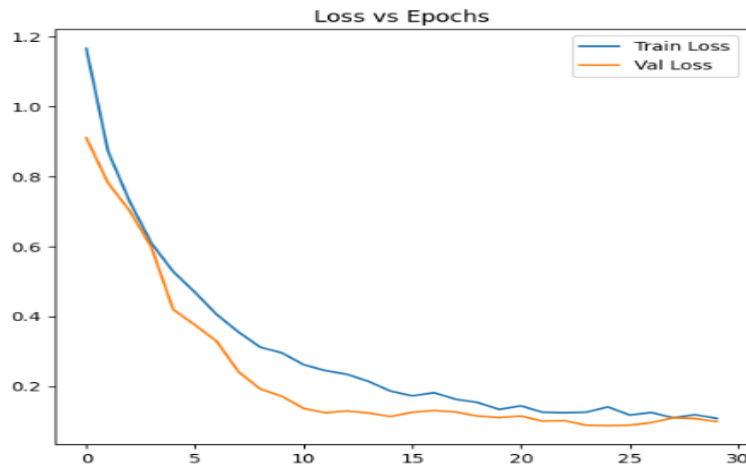


Fig3. Graphs showing the comparison of training and validation loss for MobileNetV2.



VI. CONCLUSION AND FUTURE SCOPE

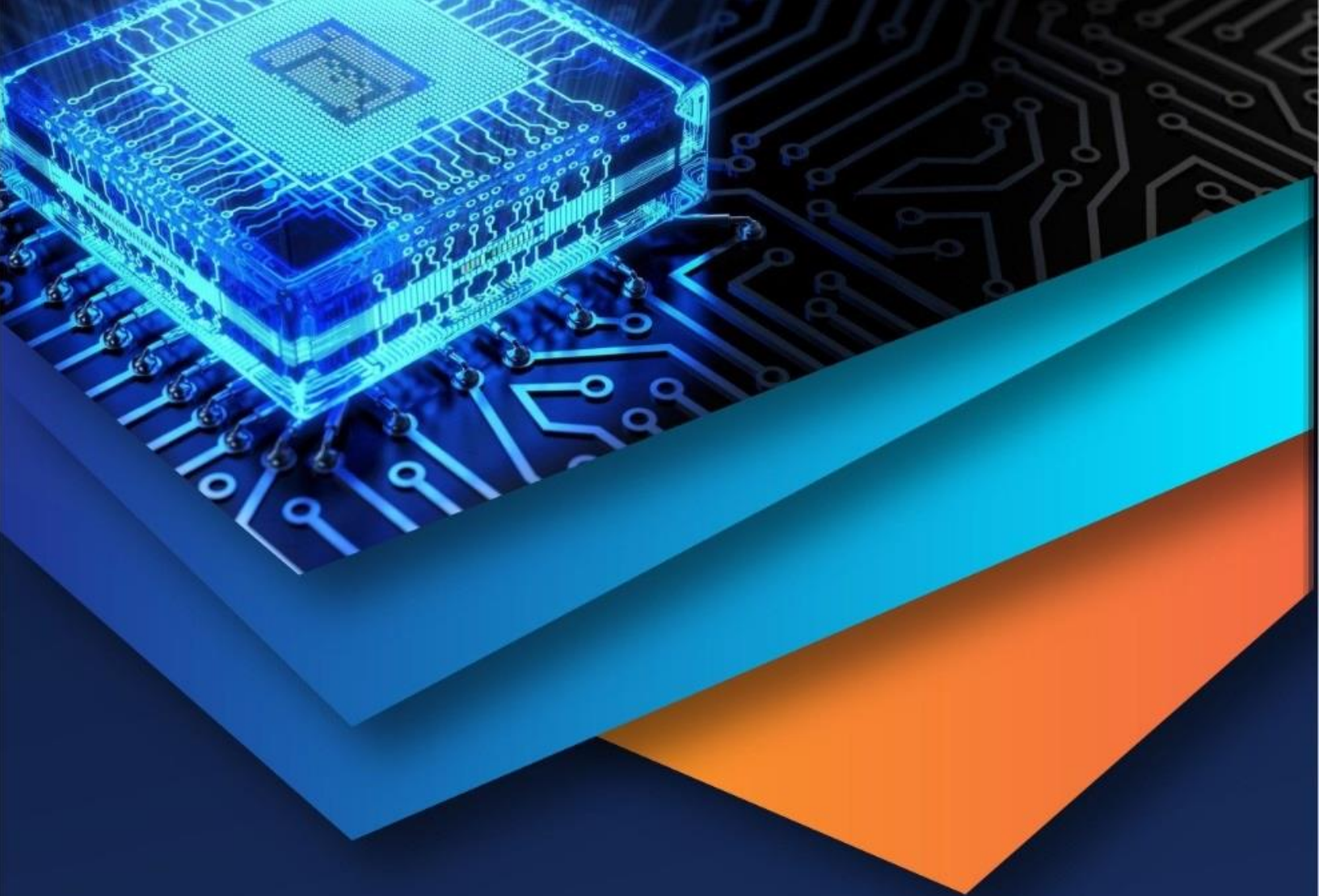
This paper presents the use of MobileNetV2 architecture in multiclass classification of Kidney CT images. The results of this study shows that a lightweight model can also give promising outcomes if finetuned carefully. It also shows that automated detection methods, aided by deep learning can decrease the probability of misdiagnosis and can enhance the quality of treatment plans. Future studies can focus on utilizing ensemble methods, explainable AI, training on complex and diverse datasets and integrating the model into real time clinical applications.

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