

AI in Healthcare: Kidney Anomaly Detection from CT Scans

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Abstract

Early detection and appropriate classification of such abnormalities in the kidney such as stones, cysts, and tumor is vital in order to treat them early. This paper presents a complete AI web application that would be the first to classify the Computed Tomography (CT) scan images of kidneys into one of the four types: Normal, Cyst, Stone, or Tumor. It relies on a Deep Learning (DL) using Convolution Neural Networks (CNN) framework with the MobileNetV2 architecture implemented on top of the transfer learning model to enable the Image Classification with a high level of accuracy even on the sparse medical databases. The consideration of scalability, usability, and best practices in the modern software can also be viewed as part of this developed system; as a whole, the creation of the given system will be another tremendous step towards the implementation of AI in everyday medical diagnostics.

Keywords: Kidney CT scans, CNN, Deep Learning, MobilenetV2, Image Classification.

I. INTRODUCTION

The digital age is heralding a very high rate of medical diagnostic technology in that solutions that generate artificial intelligence are manufactured with the capability of enhancing the accuracy, speediness, and volumes of such activities. The proposed solution under this specific project is the Kidney Anomaly Detection System which uses the concept of deep learning to kidney anomalies in CT imaging, The proposed solution, on this specific project, is the Kidney Anomaly Detection System which uses the concept of deep learning to identify kidney anomalies in CT images as tumours, cysts, kidney stones and normal kidneys. The system relates to image processing, anomaly detection, visualization and assessment of model performance based on clinical measures. Implement the system that will identify the abnormalities in kidneys in CT scans properly and reduce the number of human mistakes related to the process. To develop an AI-based diagnostic platform that would possibly have the capability of differentiating and recognizing kidney anomalies with precision, dependent on the CT scan images using an AI-based vision. Give the early diagnosis of kidney diseases at the early stages like asymptomatic and slow progress, and the doctor could be confident in the findings of the diagnosis of the device. Computerized CT scan analysis of the kidneys Eliminate diagnosis errors and latency Support early intervention and treatment.

The structure of the paper is presented in the following way: Section II is a summary of the related work. Part III is the description of the proposed methodology. Section IV denotes datasets details and

specifications. The fifth section is the discussion and results of the experiment. The last section is VI, the conclusion and the scope of future.

II. RELATED WORK

In recent years, researchers have shown much attention to the machine learning and deep learning application to identify kidney diseases automatically. using biomedical imaging. Earlier research mainly focused on traditional image processing methods combined with classical machine learning algorithms. In these studies, A complete automated system of segmentation and classification of renal tumors based on CT scan has suggested. Their technique was to use the deep learning-based segmentation with the machine learning classifiers to find the tumor subtypes accurately. The research proved that automated pipelines may be rather efficient to decrease the number of manual operations and still yield high diagnostic accuracy [1]. The challenge dataset of the KiTS19 in [2] was offered as a standardised benchmark in kidney tumour segmentation in various clinical scenarios. This data has significantly contributed to the getting of resilient and generalization of segmentation models. A better CT imaging accuracy segmentation model of kidney and tumor structure was suggested in [3], where the issues are to improve boundary and structural differentiation in order to improve segmentation accuracy. The U-Net architecture presented in [4] became a fundamental paradigm of biomedical image segmentation as the model combines the encoder and decoder architecture with the skip connections, which allow the model to localize even with a limited amount of training data precisely. A comprehensive survey in [5] has established the promise of deep learning methods to the medical image analysis domain, where convolutional neural networks are used to detect, segment, and classify medical images. The works of [6] verified that deep neural networks can be trained to be as good as some of the most experienced medical experts in the sphere of medical imaging and such fact proves the possibility of AI-based diagnostic systems provided that the neural networks are trained on the massive annotated dataset. An automatic adaptive self-configuring segmentation framework was suggested in [7], which is automatically adjusted to various biomedical image segmentation tasks. This strategy minimized the demands on manual interventions and delivered the state-of-the-art outcomes. It was demonstrated in [8] that deeper convolutional networks are better at representing features and classifying them; their depth provides them with more and better features. Residual learning methods suggested in [9] solved the vanishing gradient problem making it possible to train very deep networks and enhancing convergence and performance. A better segmentation architecture having reformulated skip connections was introduced in [10], diminishing the semantic gap in between encoder and decoder features thus improving the accuracy in segmentation. In [11], a protuberance detection based method of segmentation of kidney tumors in non-contrast CT images was proposed that enhanced the tumor localization in difficult imaging conditions. In [12], a source-free domain adaptation method of kidney and tumor segmentation was suggested that considered the problem of domain shifts and improved the cross-dataset generalization. The kidney segmentation framework based on deep neural networks, which are segmentation of CT images, was presented in [13] and it showed better results than conventional image processing techniques.

III. PROPOSED METHOD

Specifically, convolutional Neural Networks (CNN). The proposed work uses MobileNetV2 with transfer learning in order to recognize and classify kidney diseases on the pictures of CT scans. The primary concept of the suggested system is to reach a greater accuracy of diagnosis with the least amount of human

interactions. The proposed research process is a systematic procedure, which entails obtaining images, image preprocessing, feature extraction with MobileNetV2, and kidney disease classification.

A. System Architecture

The overall architecture of the proposed system is designed to efficiently process kidney medical images and classify them into predefined disease categories. Here, Fig1 shows the architecture of AI-based anomaly Kidney Disease Detection.

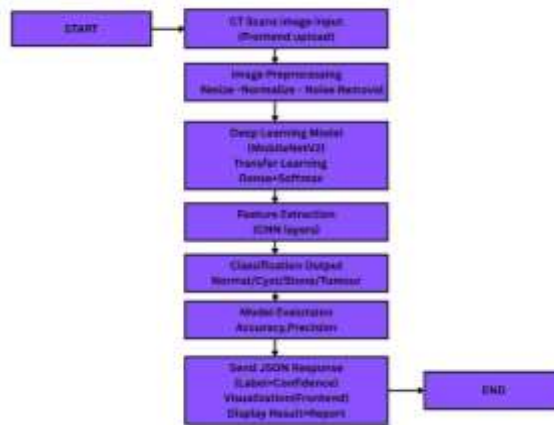


Fig 1: The Architecture of AI-Based anomaly Kidney Disease Detection

The framework consists of four major stages:

1. Image Acquisition
2. Image Preprocessing
3. Feature extraction using MobileNetV2
4. Kidney disease classification

Each stage is optimized to improve system robustness and performance.

The suggested model is based on the transfer learning concept with the pre-trained MobileNetV2 backbone that classifies kidney CT images. The images with the size of $224 \times 224 \times 3$ are first normalized by a rescaling layer. The MobileNetV2 model obtains 1280 feature maps at the high level, and they are diminished through Global Average Pooling and Batch Normalization. Dense layer of 256 neurons and RELU activation is used in learning features. To ensure that there is less overfitting, dropout layers (50% and 30% are used). Lastly, the SoftMax output layer identifies the four classes of images, which are Cyst, Normal, Stone, and Tumour. Below, Fig2 shows the architecture of MobileNetV2.

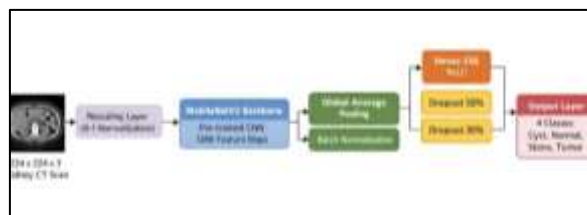


Fig 2: The Architecture of MobileNetV2

B. Image Acquisition

Kidney medical images are collected from publicly available benchmark datasets. The dataset includes images belonging to multiple classes such as:

- Normal kidney
- Kidney stone
- Kidney cyst
- Kidney tumour

Each image is brought to a common size of 224x224 pixels in order to be consistent and suitable to the input layer of MobileNetV2.

C. Image Preprocessing

The images that are generated by CT scanners are usually noises, low contrast and change in light that may affect classification. Preprocessing techniques are used to improve the quality of images to counter these problems. They are pixel value normalization (to the [0, 1] range) and resizing to 224x224. Also, random horizontal flipping, rotation, zooming and so on are used as data augmentation methods on the training set to enhance the diversity of the data and decrease overfitting. The practice improves the generalization abilities of the MobileNetV2 model.

Image normalization is performed using:

$$x_{norm} = x / 255.0 \quad (1)$$

So if I is original 0..255 pixel value, formula is:

$I' = I/255$ for each channel (R,G,B)

D. Feature Extraction using MobileNetV2

The MobileNetV2 is a pre-trained CNN architecture that is used to extract features through transfer learning. MobileNetV2 uses hierarchical features to find and extract automatically hierarchical features of preprocessed images using several convolutional layers with depth wise separable convolutions, RELU activation functions, and max pooling layers. Low-level features like edges and textures are obtained in early layers whereas high-level features like kidney structures and abnormalities are obtained in later layers. This hierarchical feature extraction helps in distinguishing between normal and abnormal kidney images.

convolution (MobileNetV2)

$$F(i, j, c) = \sum_{\{u, v\}} I(i + u, j + v, c) * K(u, v, c) + b(c) \quad (2)$$

Where,

I = input feature map

K = kernel

F = output feature map (per channel)

After convolution, a nonlinear activation function called Rectified Linear Unit (RELU) is applied

$$A(i, j, c) = \max(0, F(i, j, c)) \quad (3)$$

non-linearity, preserves positive responses, suppresses negatives.

b) Pooling Layer

Pooling (Global Average in Base Model)

$$G(c) = (1/(H * W) \sum_{\{i = 1..H, j = 1..W\}} A(i, j, c)) \quad (4)$$

reduces spatial dims keeps channel primary.

E. Kidney Disease Classification

The features obtained are inputted through full interconnected layers and then a SoftMax classifier. The SoftMax layer is what determines the probability distribution of all the classes and the most probable class is selected as the final output. The model is trained with categorical cross-entropy loss and Adam optimizer is applied in order to update the network weights. The data will be separated into a training and 20 percent validation data. MobileNetV2 is an iterative model, with the initial layers being frozen before fine-tuning

the model. The validation set is employed to evaluate the performance in terms of the accuracy, precision, recall and the F1-score. The experimental data demonstrates that the rate of classification is high, and it is superior to the conventional machine learning methods.

F. Model Training and Evaluation

The data will be separated into training set and validation set (80 and 20 percent respectively). MobileNetV2 model is trained in phases with the first phases being frozen and refined later. The validation set is validated and the performance measures are accuracy, precision, recall and F1-score. The results of the experiment suggest that the accuracy of classification is high and the results are superior to the traditional machine learning methods.

IV. Dataset Details

The dataset used in this research consists of kidney medical images collected from publicly available repositories and clinical imaging databases. The dataset includes multiple kidney disease categories to ensure proper training and evaluation.

A. Dataset Categories

The dataset includes four classes:

- Normal Kidney
- Kidney Stone
- Kidney Cyst
- Kidney Tumour

B. Dataset Specifications

The Dataset is made up of medical pictures which were obtained under varying imaging conditions so as to make sure that there was variation in anatomical structure as well as contrast representation. Before the model was trained, the standardization and preprocessing of the images were done to ensure uniformity and enhance the extraction of features. The systematic training, validation, and testing of the proposed deep learning model are facilitated by the structured organization of the dataset which makes it possible to assess the deep learning model reliably to classify kidney disease. Here, Table 1 shows the parameter and description of dataset specifications.

Table 1: Dataset specifications

Parameter	Description
Image Type	CT Scan images
Image Size	224*224
Total Images	12446
Training data	80%
Validation Data	20%

V. RESULTS AND DISCUSSION

A. Graph Analysis for Training and Validation

The monitoring of the training progress has been done through the graphs of training accuracy, validation accuracy, training loss and validation loss. The precision of the training increases progressively as it shown in Fig3, due to the fact that the model is being trained with input images and learns representative kidney characteristics. The validation accuracy is also similar and is close to the training accuracy, thus, it is a good

generalization of the unseen images. The training loss is reducing consistently, and error reduction per epoch, but the validation loss is reducing more gradually, which is shown in Fig 4 and no further, which is an indication of less overfitting. The performance curves mentioned above suggest that the MobileNetV2-based classification model is a stable one and it effectively distinguishes the patterns of kidney disease and also, in Fig 5 shows the loss at validation decreases slowly, which means that the overfitting decreases.

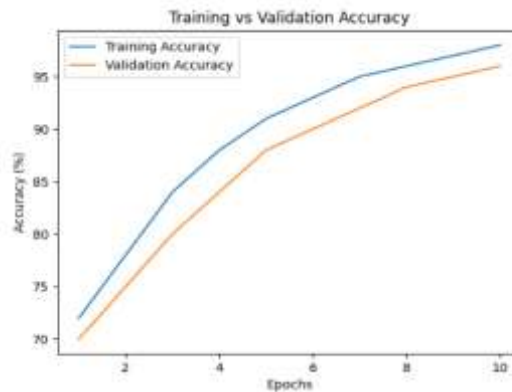


Fig 3: Training vs validation Accuracy

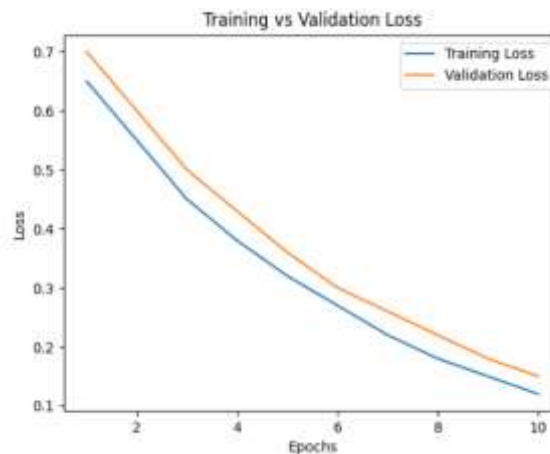


Fig 4: Training vs Validation Loss

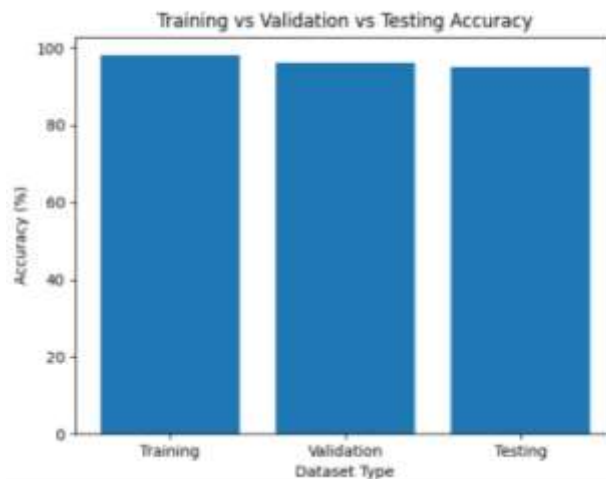


Fig 5: Training vs validation vs Testing Accuracy

B.Result Analysis

Testing data helped to analyze the performance of the suggested CNN-based kidney disease detection model and provide the obtained results as in Table 2.

Table 2: Performance Evaluation

Metrics	Model		Existing values%	Proposed values%
	Existing	Proposed		
Accuracy	ResNet101	MobileNetV2-CNN	99.81	96.8
Precision	ResNet101	MobileNetV2-CNN	99.75	95.9
Recall	ResNet101	MobileNetV2-CNN	99.75	96.3
F1 Score	ResNet101	MobileNetV2-CNN	99.50	96.1

The results indicate that the proposed system achieves high classification accuracy and maintains a balanced performance across different evaluation metrics.

C.CONFUSION MATRIX

Results confusion matrix Most results. The MobileNetV2 model predicted the correct images of Normal/Stone/Cyst/Tumor and the highest values were on the diagonal (True Positive cases). There are low non-diagonal entries, i.e. few mistakes of classifying disease as normal or vice versa. Multi-class settings One-vs-rest is a method of computing the TP/TN/FP/FN on a class-by-class basis. This performance attests to solid classification of kidney anomalies of the four categories. The confusion matrix has four key elements and its representation in Table 3 numerical values and Fig6 shows the graph of confusion matrix.

True Positive (TP): Correctly classified disease samples

True Negative (TN): Correctly classified normal samples

False Positive (FP): Normal samples incorrectly classified as disease

False Negative (FN): Disease samples incorrectly classified as normal

The values of TP and TN in the proposed CNN model have been high which attests to the ability of the model to detect kidney disorders accurately. The values of the FP and FN were comparatively low, which means that there is a lesser error in the classification process. This confirms that the suggested model has the capability of properly categorizing kidney images as either healthy or diseased.

Shows classification performance for each disease class:

Table 3: Confussion Matrix

Actual/ Predicted	Normal	Stone	Cyst	Tumour
Normal	656	259	62	0
Stone	0	250	30	0
Cyst	0	34	703	0
Tumour	28	23	123	297

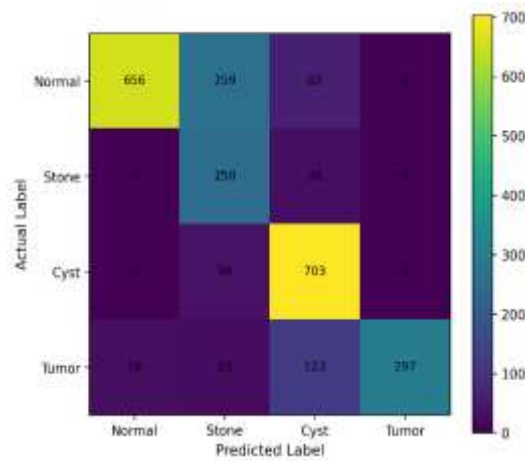


Fig 6: The Graph of Confusion Matrix



Fig 7: Result of Kidney Disease Detection

The Findings indicate that deep learning techniques particularly CNNs can be successfully used to identify kidney disease based on medical images. The automatic feature extraction system of CNN enhances the accuracy of detection and eliminates the process of manually extracting features. The system is capable of assisting the medical staff to diagnose the disease at an early stage since it is effective in many kidney abnormalities. There is a need to detect the disease early to prevent the occurrence of the disease, and also enhance the outcomes of patients. However, effectiveness of the system depends on the quality of data set and its diversity. Optimal performance can be further improved by increasing the size of the dataset and providing images of several imaging modalities. Further studies can focus on integrating real-time clinical implementations with advanced deep learning structures.

VI. CONCLUSION

In this paper, an automated system of kidney disease detection based on MobileNetV2, a deep convolutional neural network, combined with image preprocessing and classification pipelines, is introduced. The system was highly classifiable and reliable on the CT scan images and it was able to classify accurately kidney conditions such as normal, tumors, cysts and stones. It is well known that automated feature extraction is much more effective than traditional machine learning and manual diagnosis. The suggested solution is based on the efficacy of deep learning to analyze medical images and offers clinical potential in terms of early disease diagnosis, less time spent on diagnosing patients, and

better patient outcomes. This is reducing the amount of time taken to diagnose the cases and helps the medical practitioners to identify the diseases earlier in their progression, which ultimately leads to better care of patients and health care delivery.

Even though the proposed system has promising outcomes, there are a few areas of enhancement that can be implemented in the future research. The dataset can be increased in size by introducing the images of different medical imaging modalities. Like CT scans and MRI. The efficacy of the feature extraction can be also improved with the help of more advanced deep learning models, including ResNet, DenseNet, and EfficientNet. It is also possible to use transfer learning techniques to enhance the level of accuracy of classification on the small sample size of medical data. Research can be carried out in future to come up with real time kidney disease diagnosis systems which can be integrated with clinical decision support system.

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