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MULTICLASS CLASSIFICATION OF KIDNEY STONE,CYST,TUMOR AND NORMAL USING DEEP LEARNING

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Abstract : One of the major challenges in giving proper treatment is fast and accurate diagnosis of the disease.The main purpose of this project is to propose the best tool for kidney problem identification, to reduce the diagnosis time and to improve the efficiency and accuracy. In this project we have used Deep learning for classification and where we have used VGG16 and ResNet50 for Multiclass Classification task. It aims to classify people as healthy or patient individuals according to the status of Kidney.

Index Terms – VGG16, ResNet50, CNN, CT data set.

I. INTRODUCTION

Solid mineral deposition inside the kidney is the primary cause of kidney stone disease (KSD), which is a prevalent ailment. The disease prevalence varies, based on socio demographic, lifestyle, dietary, genetic, gender, age, environmental and climatic factors, but has been continuously increasing worldwide. Kidney Stone Disease (KSD) has a high recurrence rate of approximately 11% within two years after the removal of the stone. These stones are formed by solid mineral deposits that attach to the renal papillae or are found free in the renal calyces and pelvis. They are composed of crystalline and organic components and occur when the urine becomes supersaturated with a particular mineral, with calcium oxalate being the primary constituent of most stones. Stone formation is becoming more prevalent, with rates reaching up to 14.8%, and there is a recurrence rate of up to 50% within five years after the initial episode. Risk factors associated with stone formation include obesity, diabetes, hypertension, and metabolic syndrome. Stone formation can lead to chronic kidney disease, end stage renal disease, and hypertension. Kidney Tumor are a type of cancer that is more likely to develop in people of advanced age. Renal cysts (kidney cysts) are sacs of fluid or round pouches of fluid in kidneys.

Detecting disease in the kidney can be a challenging task due to the heterogeneous structure of the organ. To improve the accuracy of diagnoses made by radiologists, there is a need for more efficient models and methods that can provide assistance in making precise decisions. Diagnosing kidney stone disease involves the use of multiple imaging techniques, which require the expertise of specialists to interpret and provide a comprehensive diagnosis. To support clinicians in their diagnosis, computer aided diagnosis systems can serve as practical auxiliary tools. Recently, many studies have been conducted in which diseases were diagnosed with the deep learning methods. Along with deep learning, computer vision can categorize the images, extract the properties of an image and enable the classification of images by predicting them based on the model it creates. The proposed approach in this study involves the use of deep learning, which has shown significant advancements in the field of artificial intelligence, to automatically detect the presence or absence of kidney stones in Computed Tomography (CT) scans.

II. LITERATURE REVIEW

Paper [1],investigated the success of a deep learning model in detecting kidney stones in different planes according to stone size on unenhanced computed tomography (CT) images. This retrospective study included 455 patients who underwent Kidney stone diagnoses were based on their observation in the renal collecting system and on the measurement of Hounsfield units on unenhanced CT images. The number of patients and CT images with andwithout kidney stones in the three groups according to the sizes of kidney stones evaluated using the deep learning algorithm are presented. Training and testing were performed in the three planes and among the three study groups using the Fastai (v2) library and the Google Collaboratory platform. They used the Adam algorithm as the optimization algorithm. The sagittal-plane images on CT had higher diagnostic accuracy rates than those of other planes. Using these methods, the waiting time for results and cost of diagnosis can be reduced, and early diagnosis can be achieved, resulting in prompt management.

A deep analysis of stone detection in kidneys with image processing techniques using CT images was proposed in [2]. This research explored the advanced technique to detect boundary, segmented area, and enhance detection of stone location from the kidney. This investigation helped in identifying the location of stone based on pixels. The investigation showed this research has 92.5% accuracy with an effective stone detection technique. These studies investigate four stages, image pre-processing, segmentation of image using K-means clustering, detection of stone location through the kidney, and classification. Pre-processing is a method for removing background noise from images. To remove noise from CT scan images the median filter was used. The result display stone detection in kidneys with image processing techniques using CT images.

A 2D-CNN model was proposed in [5] which had three models concerning with Kidney Tumor detection such as a 2D convolutional neural network with sixlayers (CNN-6), a ResNet50 with 50 layers, and a VGG16 with 16 layers. The last model wasused for classification as a 2D convolutional neural network with four layers (CNN-4).A dataset from the King Abdullah University Hospital (KAUH) was collected that consisted of8,400 images of 120 adult patients who have performed CT scans for suspected kidney masses. The dataset was divided into 80% for the training set and 20% for the testing set. Theaccuracy results for the detection models of 2D CNN-6 and ResNet50 reached 97%, 96%, and60%, respectively. At the same time, the accuracy results for the classification model of the 2D CNN-4 had reached 92%.

A segmentation based kidney tumor classification using Deep Neural Network (DNN) was used in [7].It had two steps. Firstly, the kidneys were segmented using a manual segmentation technique and trained UNet along with SegNet for kidney segmentation. Then, for the classification task, the modified MobileNetV2, VGG16 and InceptionV3 was trained on the segmented kidney data. Normal-Cyst-Tumor and Stone dataset(published in Kaggle) was used to train ourmodels. Finally, the classification models MobileNetV2, VGG16, InceptionV3 scored with 95.29%, 99.21% and 97.38% accuracy on test set. It was found that the modified VGG16 model has the best accuracy and the highest sensitivity and specificity.

III. Proposed Methdology

In this project we have proposed a system where we have used deep learning for classification of kidney stones, cysts, Tumor and normal and we have used pretrained model for classification task. A dataset namely “CT KIDNEY DATASET: Normal-Cyst-Tumor and Stone” is collected and annotated with 12,446 images utilizing the whole abdomen and the neurogram protocol. The CNN-based deep learning models (i.e., VGG16 and Resnet50) using transfer learning approach are applied to detect kidney abnormalities and presented a thorough performance study.

1)Data Acquisition: The dataset is collected from Kaggle, ensuring that the images are labelled as either kidney stones, cysts, tumors and normal tissue.

2)Model selection: Choosing a pretrained model architecture that is appropriate for the classification task. We have chosen VGG16 and ResNet50 for classification. The pretrained model should be capable of learning complex features from medical images.

3)Feature Extraction: Using pretrained model to extract the features from the dataset of medical images. This involves passing images through the pretrained model and obtaining the output probabilities for each class.

4)Model evaluation: Evaluate the pretrained models’ performance on separate validation dataset to determine its accuracy.

5) Comparison and Analysis: The performance of the VGG16 and ResNet50 models are compared to determine which model performs better for the given task. The results are analyzed to identify the strength and weakness of each model.

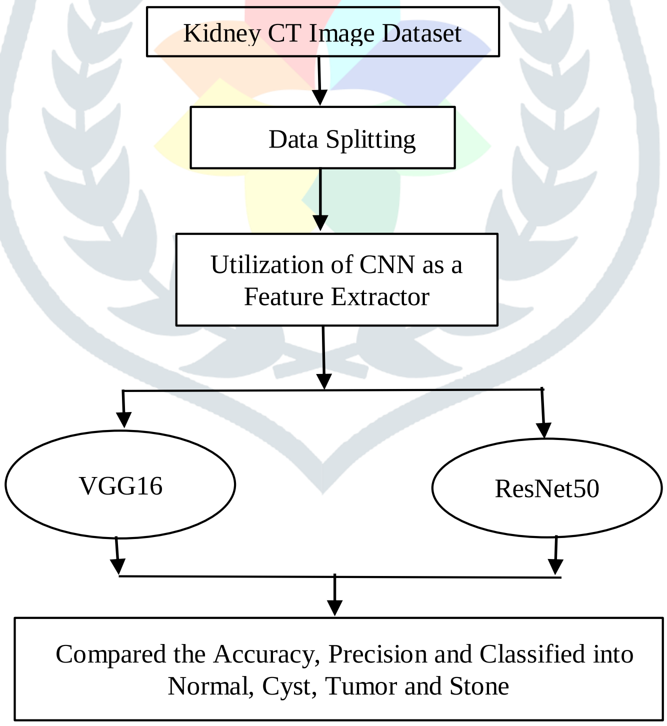

Fig 3.1 Flowchart

IV. RESULTS

This method is carried out using Jupyter notebook to run and compile the program. The Results obtained were in the form of Conclusion matrix Heat Map in which distribution of Kidney stone. VGG16 and ResNet50 can be used for the multiclass classification of kidney stone, cyst, tumor, and normal cases using deep learning by using the models as feature extractors, training the model on the preprocessed dataset. The performance of the models is evaluated on the test set, and the results are compared and analyzed to determine which modelis better suited for the given task.

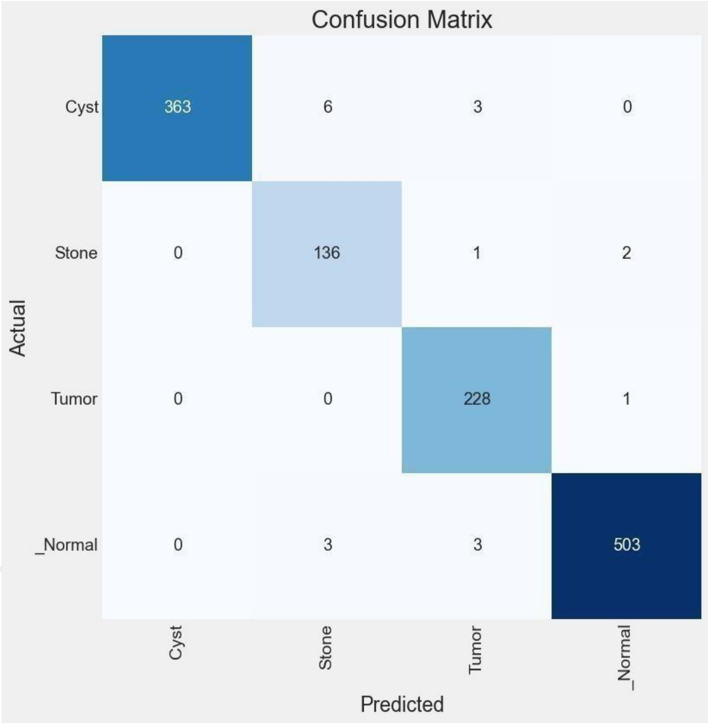

Fig 4.1 Confusion Matrix

Fig 4.2 Graph Representing Training and Validation Loss

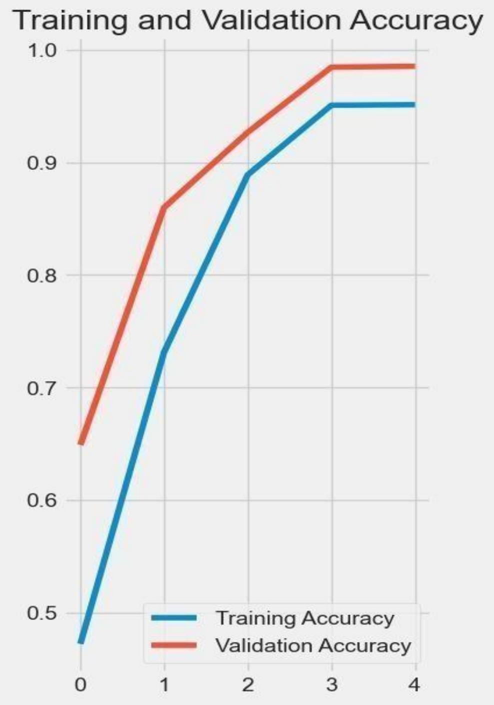

Fig 4.3 Graph Representing Training and Validation Accuracy

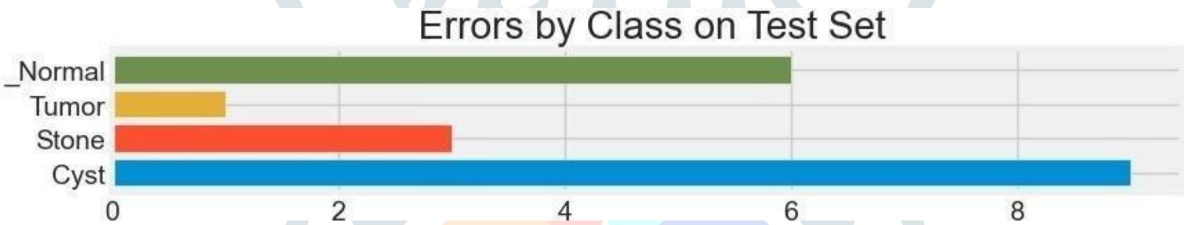

Fig 4.4 Analysis of Error by Class on Test set

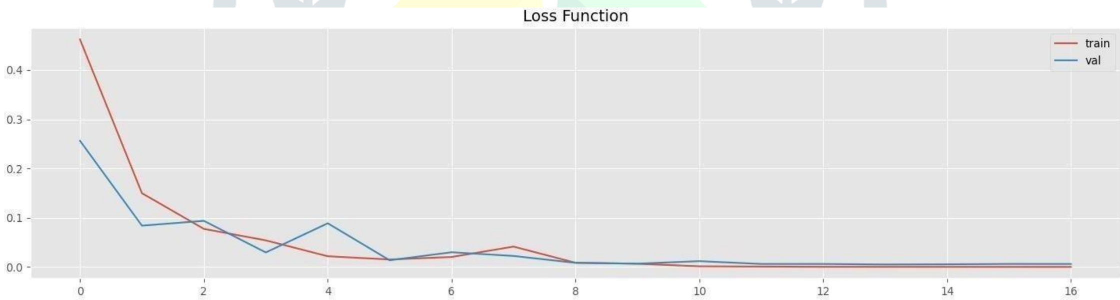

Fig 4.5 Graph Representing Loss Function

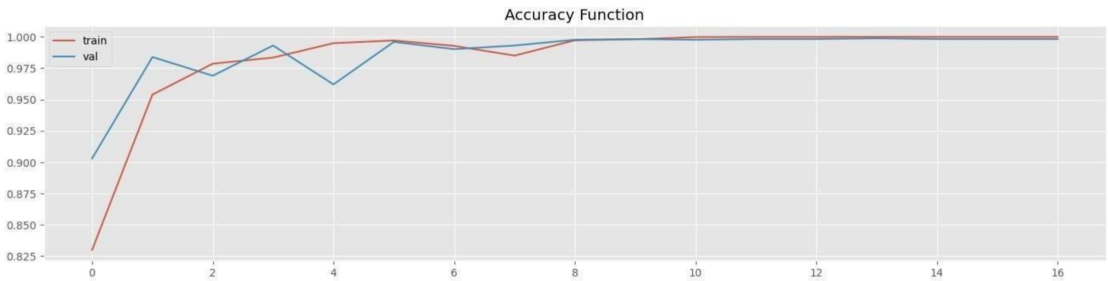

Fig 4.6 Graph Representing Accuracy Function

	Precision	Recall	F1-score	Support
Cyst	1.00	0.98	0.99	372
Stone	0.94	0.98	0.96	139
Tumor	0.97	1.00	0.98	229
Normal	0.99	0.99	0.99	509
Accuracy			0.98	1249
Macro avg	0.98	0.98	0.98	1249
Weighted avg	0.99	0.98	0.98	1249

Table 4.7 Result obtained using VGG16

	Precision	Recall	F1-score	Support
Cyst	1.00	1.00	1.00	1126
Stone	0.99	1.00	0.99	425
Tumor	1.00	1.00	1.00	659
Normal	1.00	1.00	1.00	1524
Accuracy			1.00	3734
Macro avg	1.00	1.00	1.00	3734
Weighted avg	1.00	1.00	1.00	3734

Table 4.8 Result Obtained using ResNet50

The performance analysis for the predicted matrix have calculated based on confusion matrix. For confusion matrix, true positive, true negative, false positive and false negative, values arecalculated from the prediction matrix on the validation of CKD. Precision and recall are calculated for each class separately.

In the classification report Precision and recall values are present for each class, but not for the overall accuracy because accuracy is an overall measure of performance that takes into account all classes.In multiclass Classification ,F1 score and Support values for accuracy are calculated by taking the weighted average overall classes.

The performance measures have calculated :

Accuracy = TP+TN / (TP+TN+FP+FN)

Precision = TP/(TP+FP)

Recall=TP/(TP+FN)

F1 score = 2*Precision*Recall / (Precision + Recall)

V. Conclusion

This approach has the potential to reduce both the waiting time for results and the cost of diagnosis and early diagnosis can be achieved, resulting in prompt management. With the help of fully developed fully kidney disease detection system, the workload of the radiologists can be reduced.

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