Kidney Stone Detection using Deep Learning Techniques

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***Abstract*—Healthcare sector is a broad field offering diverse facilities which includes diagnosis of medical issues, offering advanced treatments and surgeries to ensure the wellness of a patient. Due to the ever increasing health issues, there are lot of new challenges encountered by the medical sector. To overcome this challenges, deep learning techniques have become an integral part of the medical field aiding in medical image analysis offering valuable insights for diagnosis of diseases. Kidney Stone detection involves deep learning models to analyse the Computed tomography scans of patients to accurately identify the of kidney stones. The models are trained using various pre-processed cross-sectional CT scans of each patient, allowing the model to comprehensively analyze and learn from diverse imaging data for enhanced diagnostic accuracy and effectiveness in detecting and classifying into kidney stones , cysts, tumors and normal conditions along with the identification of kidney stone sizes.**

***Index Terms*—Kidney Stone Detection, Deep Learning, Health Care Sector, Medical image processing.**

I. Introduction

The healthcare domain is an enormous field that offers a wide variety of services, primarily including the diagnosis of medical issues, health monitoring, curative services, regular health assessments, and paramedical aid. In the current generation, various aspects such as environmental factors, urbanization, the adoption of improper lifestyles, and dietary plans stand as the primary causes for having a hazardous impact on human health, leading to various health complications. To address these challenges, the healthcare sector needs to put in continuous efforts to integrate innovative technologies and solutions for effective diagnosis and remedying the increasing prevalence of chronic diseases.

Deep Learning, a cutting edge technology,mimics the workings of the human in processing data and capturing patterns for decision making. It is immensely used for analyzing medical image records of patients which aids in the diagnosis and treatment of various diseases fostering the development of personalized plans for healthcare. Various diseases related to heart, cancer, skin, eye and other infectious diseases can be identifying at the earliest with a great ease. The ability to assess the health records and scans aids in recognizing the underlying patterns and correlations which are beyond the scope of human detection.The real time analysis of the medical images significantly improves the efficiency and diagnostic accuracy of medical procedures.

Kidney Stone

Kidney stones is a medical condition where hard solid wastes made of minerals and salts are formed inside the kidneys, often causing pain when passing through the urinary tract. Deep learning models have transformed the analysis of computed tomography scans and enhanced the precision and accuracy of identifying stones of various sizes and composition in kidneys.

Fig. 1. CT image of Kidney Stone

Kidney Cyst

A fluid filled pockets in kidney is called Kidney Cyst, which can be developed on or inside the kidney. These kind of kidney cysts called as simple kidney cyst occurs more frequently, kidney cyst obstructs the natural flow of blood or urine in kidney. Kidney cysts are treated using a procedure called Sclerotherapy.

Kidney Tumor

A group or mass collection of abnormal cells that form on kidney is called Kidney Tumor. It might be non-cancerous(benign), they are usually smaller in size (less than 1.6 inches). Benign won't spread to other parts of body, Cancerous(malignant) are large kidney tumors (greater than 1.6 inches), it grows quickly and spreads to other parts of body. Kidney tumor is also called as renal tumors.

This study focuses on developing an automated system for detecting the presence of kidney stones by assessing various cross sectional CT scans of each patient using deep learning algorithms. The algorithms classify the images into kidney stones, cysts, tumours and normal conditions along with the identification of the sizes of the stones formed which makes it a easier task for health care centers to detect kidney stones presence and initiate the appropriate therapy swiftly.

II. Literature Review

This section summarizes the insights obtained from the survey of various papers on the topic of kidney stone detection using deep learning techniques. KK Patro et al.[1] A model under deep learning has been created that can detect kidney stones with a success rate of 98.56%. The inclusion of Kronecker convolutions has improved the performance of CNN in identifying kidney stones. For the detection of kidney stones, a deep learning technique that incorporates Kronecker convolutions has been utilized. The utilization of Kronecker product-based convolution has resulted in a reduction in the redundancy of feature maps. In the evaluation of the model, various metrics like accuracy, precision, recall, and F1 score have been taken into account. Through the analysis of CT scan images, the automated model has got an accuracy of 98.56% in detecting the kidney stones. This system has proven to be more effective than recent techniques in the identification of kidney stones.

S Jain et al.[2] The outcomes of this research involve the enhancement of image quality, detection, and classification of kidney stones using CT scans. The algorithm's ability to generate high-quality images is assessed using various metrics such as SSIM, PSNR, Entropy, FSIM, NCC, and NAE. A combination of threshold segmentation and watershed algorithm is used to identify kidney stones. These evaluation metrics are used to assess similarity, texture, contrast, and luminance in the processed images. Pre-processing techniques are used to enhance stone detection accuracy. The effectiveness of the stated approach has been proven by comparing it to current algorithms. The technique suggested is intended to increase the accuracy and reliability of kidney stone detection.

V Karthikeyan et al.[3] A CNN model was proposed to accurately detect kidney abnormalities in CT scans. An end-to-end CNN model was proposed for specifically detecting kidney abnormalities. The evaluation of this model includes accuracy, recall, specificity, precision, and F1-measure. A detection rate of 99.17% was achieved in validation tests using CT scans. The model demonstrated an accuracy of 99.68% when tested with different dataset samples. The validation process using a clinical dataset resulted in a prediction accuracy of 99%. The proposed CNN model shows high accuracy in detecting kidney abnormalities, with evaluation indices including accuracy, recall, specificity, precision, and F1-measure.

N Sasikaladevi et al. [4] Deep learning techniques are employed to detect chronic kidney disease (CKD) at an early stage using radiology images. The process involves constructing a hypergraph and utilizing a convolutional neural network for representational learning. The model is evaluated against the most recent techniques in diagnosing kidney stones, cysts, and tumors. It employs different measures like precision, recall, accuracy, F1 score, sensitivity, specificity, and F1 score to confirm its effectiveness. With a remarkable validation accuracy of 99.71 percentage, it outperforms other algorithms, establishing itself as a dependable digital replica for prompt detection of kidney ailments.

S Santhosh et al. [5] Detection of kidney stones using CT scan images is the main focus. To achieve this, a hybrid CNN-SVM model is used along with image processing techniques. The dataset used for classification includes cysts, tumors, and kidney stones. To improve the quality of CT images, noise removal techniques are applied. A hybrid model that combines CNN and SVM is employed for kidney stone detection. SVM is utilized for both classification and regression tasks in the diagnosis of kidney stones. Metrics such as accuracy, precision, recall, confusion matrix, and loss are used for evaluation.

B Manoj el al. [6] An automated system was developed to detect kidney stones using deep learning models. The VGG series model achieved 99% accuracy in identifying kidney stones out different Deep Learning models like Xresnet50 Xresnet101 Densenet201 Resnet34 Resnet50 Resnet101. The Grad-CAM technique was used to locate the affected area. Data augmentation techniques like rotation and zooming were used to increase the dataset size. The dataset size was increased from 1453 to 3265 images through augmentation techniques. Deep learning models effectively classify images using evaluation metrics such as accuracy, precision, recall, F1 score, and ROC-AUC. The VGG16 architecture achieved 99% accuracy in detecting kidney stones. These models automatically classify normal and kidney stone images. Augmentation techniques not only increase the dataset size but also improve the models' performance.

DC Elton et al. [7] A deep learning system improved the detection and segmentation of kidney stones on noncontrast CT scans, indicating potential for automated volume monitoring. The system achieved high sensitivity (0.86) with minimal false positives, strong correlation with manual measurements (r2= 0.95), and an area under the receiver operating characteristic of 0.95. It utilized a 3D U-Net architecture for kidney segmentation and a 13-layer convolutional neural network for stone detection, integrating various techniques for accurate analysis.

K Yildirim et al.[8] The paper concentrates on the application of deep learning in the automated identification of kidney stones. Coronal CT images are employed to achieve a precise detection of kidney stones. The implementation of a deep learning model has resulted in a remarkable 96.82% accuracy in the identification of kidney stones. The model has successfully identified small kidney stones with a sensitivity of 95%.

M Akshaya et al.[9] The effectiveness of Back Propagation

Network in the detection of kidney stones is well-established. The accuracy of kidney stone classification can be greatly improved by using image processing techniques, specifically by incorporating feature extraction. The utilization of Back Propagation Network remains a reliable method for kidney stone detection. Feature extraction techniques employed in image processing contribute to the enhancement of accuracy in the classification of kidney stones.

III. Research Gap

The authors[1] focuses on reducing the computational complexity of Kronecker convolution and conducting an ablation study to assess the significance of individual components, like Kronecker convolution, in the proposed deep learning model.

The paper[2] requires for more efficient kidney stone detection and segmentation methods and over-segmentation issue in watershed algorithm needs to be addressed.

The research[3] lacks testing AI models for stone categorization success. Failure to consider stone composition, crucial for treatment.

The limited exploration of shallow deep learning models for classifying kidney CT images with ideal accuracy. Existing studies [4] have focused on dense models like ResNet50, VGG16, VGG19, Xception, and InceptionV2, which require high computational resources and time. We need more efficient models that can achieve accurate classification without excessive complexity. The proposed methodology introduces a hyper-graph convolutional neural network (HGNN) designed specifically for renal disease classification. This approach aims to reduce training and testing time while maintaining high accuracy levels compared to traditional deep learning models.

The research gaps in kidney stone detection using CT scans include the need to explore ensemble learning techniques, consider transfer learning for model improvement, and optimize pre-processing techniques to enhance diagnostic accuracy and efficiency[5].

It requires for automated systems to detect kidney stones accurately [6]. Potential for deep learning models to enhance kidney stone detection. has context menu.

[7] The research gap includes Limited works on computer-aided detection of kidney stones in CT and few systems segment stones for volume measurement in CT scans.

[8] The research gap noted is mis-classification due to stone location outside the kidney and the importance of understanding criteria in deep learning black-box structures.

The research gap observed in [9]is human examination for kidney stone detection lacks accuracy and Noise in MR images from operator errors causes classification inaccuracies.

IV. Materials and Methods

The proposed model for the detection of kidney stones involves a robust approach, and various pre-processing and post-image processing techniques. The various methods and models are tested and trained on the given dataset using the open source online platform to run Python codes - Google Colab. Its

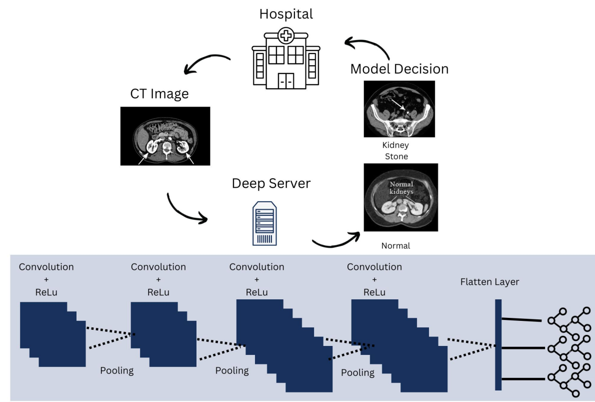

Fig. 2. Proposed Model for Kidney Stone Detection

interactive nature enables researchers and developers to experiment with various models, parameters, and data pre-processing steps, promoting a streamlined and collaborative approach to creating effective and efficient deep learning algorithms for kidney stone detection. The approach encompasses a range of pre-processing techniques such as grayscale conversion. Convolutional neural networks (CNNs) such as GoogLeNet, MobileNet, DenseNet, SENet, and generic CNN are utilised in kidney stone identification. For this objective, each architecture has benefits of its own. DenseNet encourages feature reuse, SENet increases representational power, GoogLeNet strikes a compromise between depth and effectiveness, MobileNet is appropriate for contexts with limited resources, and generic CNNs provide a standard for comparison. Deployment needs and computing resources are two examples of elements that influence architectural selection, Fig.2 explains the work flow of the model with the inner layers of the CNN model used.

V. Methodology

A. Dataset Description

This dataset considered is obtained from the Picture Archiving and Communication System (PACS). It includes a collection of 12,446 unique Dicom images from patients who are diagnosed with kidney-related conditions, including kidney tumors, kidney cysts, kidney stones, and normal. The dataset is meticulously verified by radiologists and medical technologists for accuracy and comprises 3,709 images of cysts, 5,077 of normal findings, 1,377 of stones, 2,283 of tumors which helps in offering a comprehensive resource for deep learning applications in the detection and diagnosis of kidney-related anomalies.

B. Pre-processing Stage

Pre- processing steps in kidney stone detection includes important procedures including resizing and zooming. By

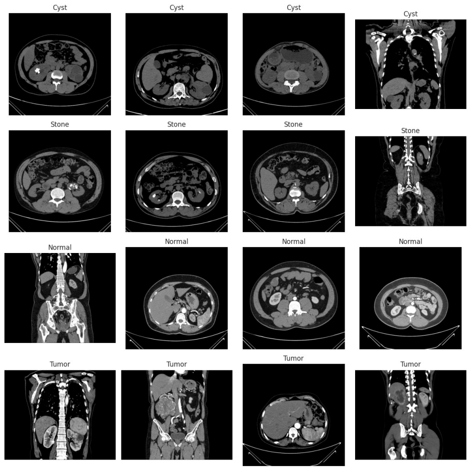

Fig. 3. CT image of Kidney Stone

using interpolation techniques like closest neighbour or bilinear, resizing picture size for consistent analysis and computing efficiency. By zooming the image, the model identifies minor structures more accurately. Among the methods are dynamically applying scaling factors or resizing. These preprocessing steps enhance the quality of the images and make further analysis easier, leading to better diagnostic result.

C. Data Visualization and Resizing

Figure.4 shows the metadata of the dataset used for detecting kidney stone, the graph shows the distribution of different classes. Among all the classes normal is higher followed by cyst. The CT scan images in the dataset are

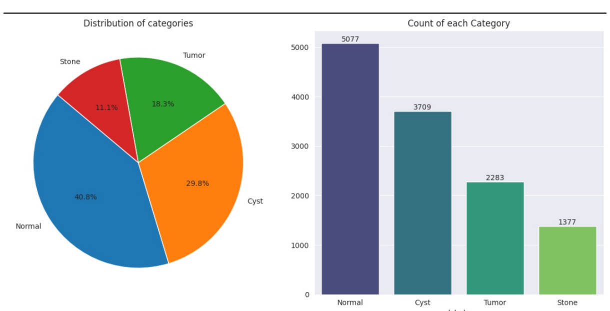

Fig. 4. Graphical Representation of Data

of different sizes, which leads to computation deficiency. By helping to normalise pixel levels to 150x150 pixels, the resized pictures improves the performance of models during training and inference while also promoting more consistent data representation.

D. Convolutional Neural Network

The convolutional layer would be tasked with extracting relevant features from the kidney CT scan images. Imagine tiny filters scanning the image, identifying edges, shapes, and textures that might indicate the presence of a kidney stone.After the convolutional layers extract features, pooling layers come into play. They help reduce the image's dimensionality and make the data more manageable. They achieve this by selecting the most significant information from a small region, like picking the brightest pixel from a grid of pixels. Later the ResLayer allows information to flow directly from earlier layers to later ones. This is crucial for the network to learn complex patterns associated with kidney stones. The global pool layer ensures all the extracted features are transformed into a fixed size. The data is transformed from a 3D format into a 1D vector by flatten layer. Finally the liner layer takes the flattened data and makes the classification decision. It has learned to associate the extracted features with the presence or absence of a kidney stone in the image.

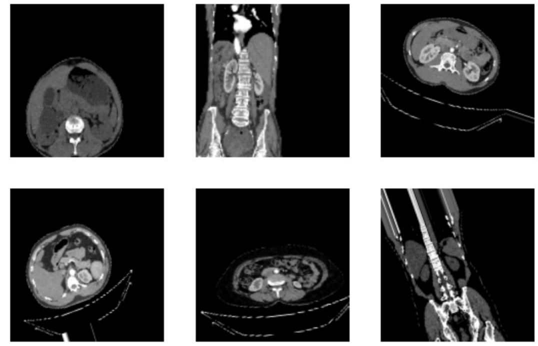

Fig. 5. Sample Picture before resizing

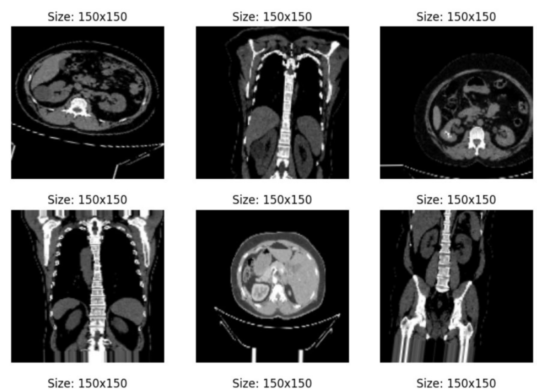

Fig. 6. Sample Picture after resizing

E. GoogleNet

A Convolutional Neural Network called GoogleNet was made to get accurate image recognition models. Through the incorporation of Inception modules in a network, convolutional filter sizes can be chosen within each block by layering the modules and utilizing max-pooling layers to decrease grid resolution by half with a stride of 2, while combining outputs from multiple filters efficiently along the depth dimension using a parallel technique.

F. DenseNet

The Dense Network (DenseNet) is that mainly uses Convolutional Neural Network and is sequential in its structure. Instead of providing each layer in the network with connections with the other layers, for each layer, there is bypass of the connection with all the other layers. DenseNet design is founded on a straightforward and basic principle: by implementing a dense block where the features outputs from the first layers are fused at every layer, the whole network becomes available for the feature extracted from all the previous layers. Such approach is obtained by possessing the "shortcut" relationship which is lead from the output of the preceding layer on every layer's input. Numbers a lot of crumbling of blocks with deep level open to feel and touch when more particles are allowed to be added.

G. SENet

A squeeze-and-excitation block is used in a convolutional neural network design called a SENet, which allows the network to dynamically execute channel-wise feature recalibration. To obtain features, the input picture undergoes a feature transformation(such as convolution process), to obtain a single value for each channel of output, the data is squeezed. Then an excitation operation is applied to the squeezed operation's output in order to get pre-channel weights. The block's final output is then generated by rescaling the feature map with these activations once the pre-channel weights are available.

VI. Results and Discussions

This section includes the description of the loss plots, accuracy plots and confusion matrix of each model along with the comparison of the valuation metrics between the models.

TABLE I
EVALUATION METRICS COMPARISON

Model	Train Accuracy	Validation Accuracy	Test Accuracy
GoogleNet	97.84%	99.83%	99.89%
Convolutional Neural Network	93.37%	92.44%	92.50%
DenseNet	99.97%	99.94%	99.89%
Squeeze-and-Excitation Networks	80.80%	80.39%	80.07%

TABLE II
EVALUATION METRICS COMPARISON

Model	Precision	Recall	F1 Score
GoogleNet	99.89%	99.89%	99.89%
Convolutional Neural Network	93.32%	92.50%	92.37%
DenseNet	99.89%	99.89%	99.89%
Squeeze-and-Excitation Networks	79.81%	80.07%	78.15%

The evaluation metrics considered for the evaluating and comparing the performance of the models include Accuracy, Precision, Recall and F1-Score.Table I includes the values of training accuracy, validation accuracy and testing accuracy of models considered. Table II compares the Precision, Recall and F1-Score of the models. Figure 7 depicts the confusion matrix which helps in analyzing the performance of GoogleNet model in classification of kidney disorders. The model correctly classified 542 cysts out of 600 without any misclassifications and all the 773 normal cases were correctly classified as normal. 223 stones were correctly classified as stone and one stone is miscategorized as tumor. One tumor was wrongly predicted as normal and the rest 327 are correctly classified as tumor.

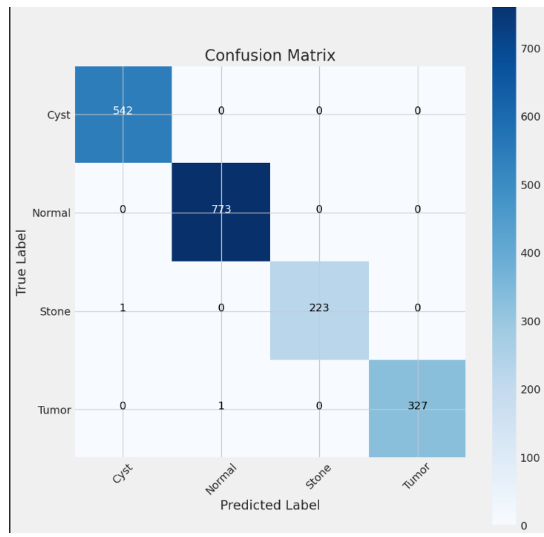

Fig. 7. Confusion Matrix of GoogleNet Model

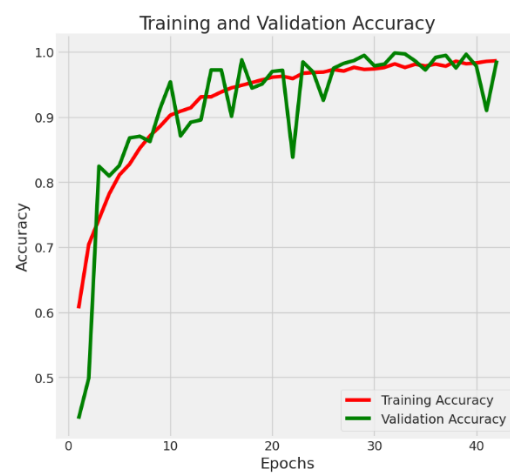

Fig. 8. Accuracy Plot of GoogleNet model

Fig. 8. represents the accuracy plot of GoogleNet model where the red line indicates the performance of the model on the training data after each epoch and the blue green line depicts the model performance on the unseen validation data.

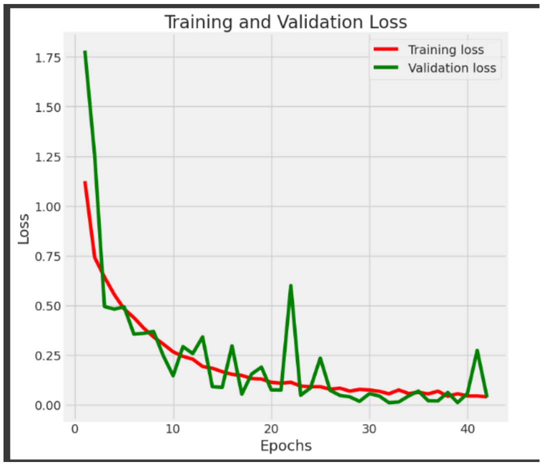

Fig. 9. Loss Plot for GoogleNet Model

The training accuracy begins around the value of 0.5 and increases to 1 in 40 epochs and almost the same trend is followed by the validation curve as well. Fig. 9. depicts the loss plot of the GoogleNet model. The red line indicating the training loss starts at the value of 1.75 and gradually comes down around the value of 0.25 and the green line depicting validation loss also follows about the same pattern as training loss.

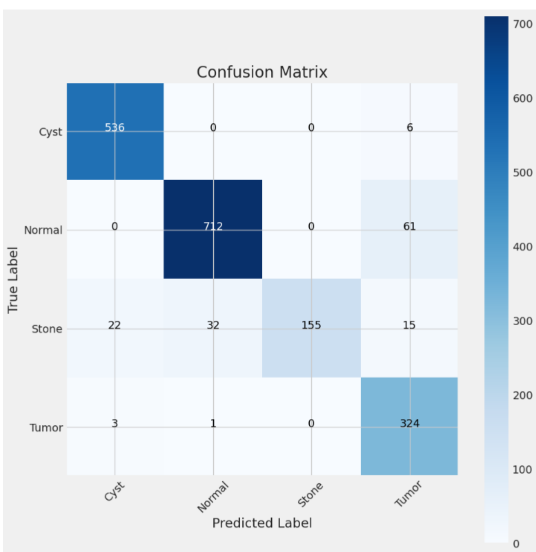

Fig. 10. Confusion Matrix of Convolutional Neural Network

Fig. 10. depicts that the Convolutional neural networks classified 536 cysts into cysts and 6 cysts are misclassified as stones. 712 of the normal conditions were classified rightly and 61 normal are wrongly classified as Tumor. 3 tumors are misclassified into cyst and 1 tumor is wrongly predicted as normal, rest of the 324 tumors are correctly classified. Finally 155 stones are perfectly classified into stones and 22 of the stones are wrongly classified as Cyst, 32 stones into normal and 15 stones as tumor.Fig. 11. is the accuracy graph generated by the CNN where the training that the training accuracy starts at the value of 0.65 and ranges upto 1 in 30 epochs and the validation accuracy ranges from 0.43 to almost 1 in 30 epochs.in Fig. 12. shows that training loss decreases from 0.77 to 0.02 and validation loss decreases from 1.74 to 0.25 in 30 epochs.

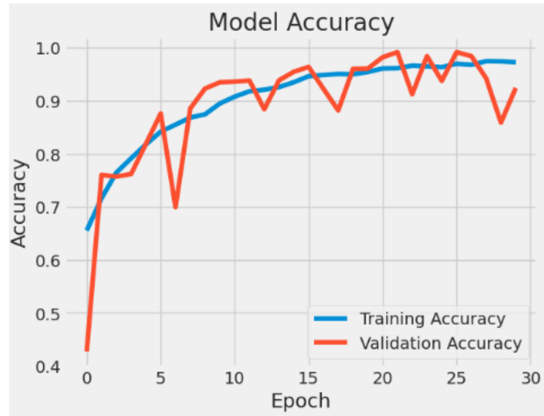

Fig. 11. Accuracy plot of Convolutional Neural Network

The confusion matrix in Fig. 13. shows that the DenseNet model correctly classified 542 cysts, 772 normal, 220 stone and 324 tumor. 1 normal is misclassified as cyst, 4 stones are wrongly predicted as cysts and 4 tumors are wrongly predicted as cysts. Fig. 14. represents the accuracy plot of the DenseNet model where the training accuracy increases from 0.66 to 1 and the validation accuracy is increasing from about 0.78 to 1 in 18 epochs. The loss plot depicted in Fig. 15. shows that the training loss decreases from 0.6 to 0 and validation loss changes from 0.8 to 0 over 18 epochs.Confusion matrix in Fig. 16. depicts that the SENet models has correctly classified 541 cysts, 732 normal , 57 stones and 173 tumors. Several normal conditions, stones and tumors have been misclassified by the model. The accuracy plot of SENet model in Fig. 17 shows that the training accuracy begins from about 0.52 and exceeds 0.8 after 50 epochs.The validation accuracy starts from 0.6 and goes above 0.8 over 50 epochs.The loss plot in Fig. 18.

Fig. 12. Loss Plot of Convolutional Neural Network

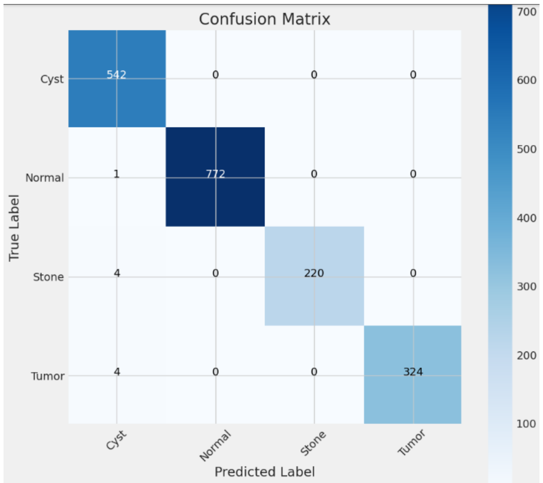

Fig. 13. Confusion Matrix of DenseNet

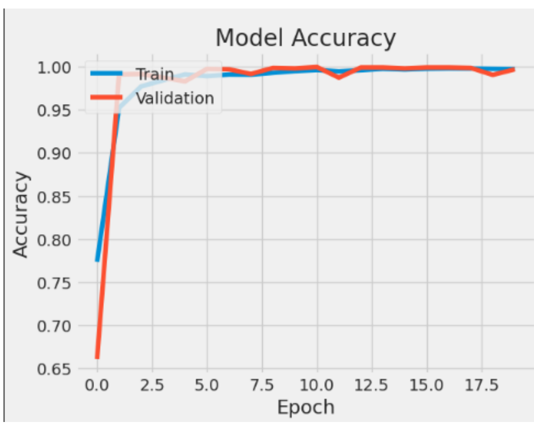

Fig. 14. Accuracy Plot of DenseNet

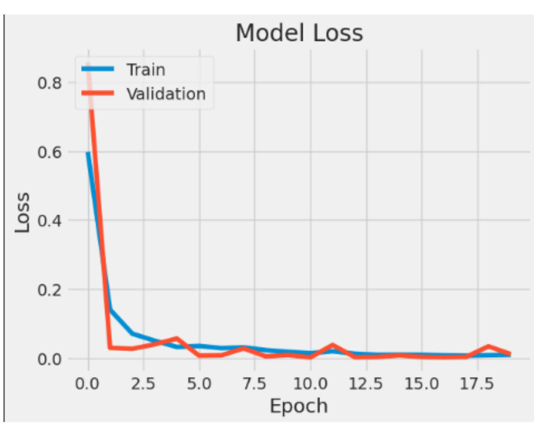

Fig. 15. Loss Plot of DenseNet model

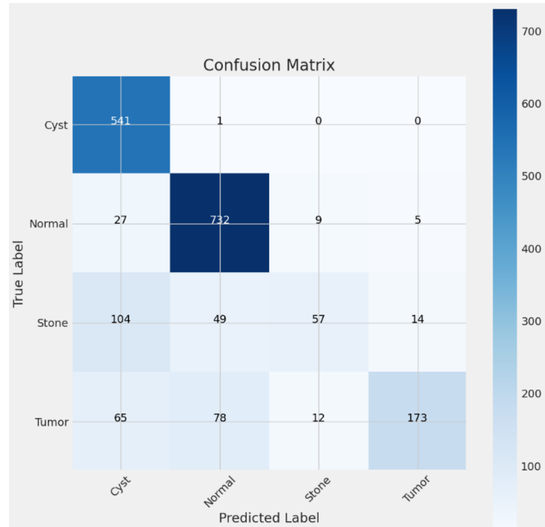

Fig. 16. Confusion Matrix of SENet

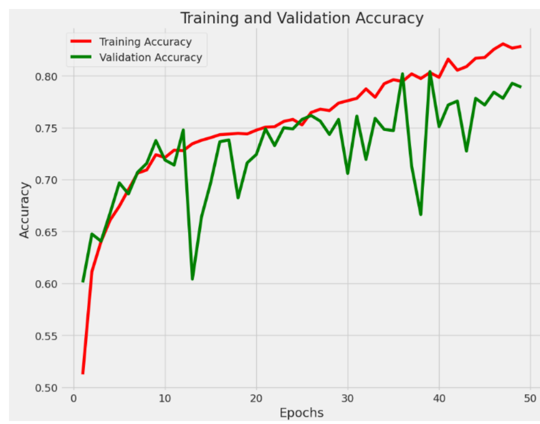

Fig. 17. Accuracy Plot of SENet

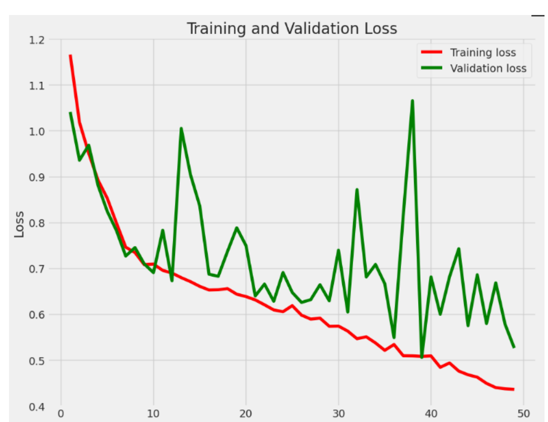

Fig. 18. Loss Plot of SENet

shows that the training loss decreases from about 1.18 to 0.42 and validation loss decreases from about 1.03 to 0.43 in 50 epochs.

By analyzing the evaluation metrics and the plots, the best models for classifying kidney disorders is DenseNet model and GoogleNet model with high precision, recall and f1 score values of 99.89% each.The DenseNet model also exhibits high accuracy values of Train Accuracy: 99.97%, Validation Accuracy: 99.94% and Test Accuracy: 99.89%.The Google Net model exhibits high values of train validation and test which are Train Accuracy: 97.84%, Validation Accuracy: 99.83% and Test Accuracy: 99.89% as shown accuracy plots.These values indicates that effective and reliable predictions by the models.The loss percentage is about 0.2% for the DenseNet model and about 2.3% for the GoogleNet model which indicates that classification made by the model are accurate. The Convolutional Neural Network model has lower values of performance metrics compared to DenseNet and GoogleNet models but has showcased better performance in comparison to the SENet model.

VII. Conclusion

The paper focuses of the classification of Kidney Disorders into Kidney Sone, Tumors, Normal condition and Cysts using Deep learning models such as Convolutional Neural Networks,GoogleNet , DenseNet and SENet. A comparative analysis of the performance of the models is done by evaluating the Accuracy, Precision, Recall and F1-Score and by analysing the accuracy plots and loss plots of each model is done. DenseNet and GoogleNet model have made the most accurate predictions in classifying the kidney disorders, followed by Convolutional Neural Networks then the SENet model.

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