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Kidney Disease Classification

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***Abstract*— The analysis of any clinical situation fast and efficaciously offers one in every of the largest boundaries to imparting suitable care. The important intention of this task in figuring out renal problems, primarily based totally on the CT photographs of kidney, and growth effectiveness and accuracy. In this research, we hired deep gaining knowledge for the multiclass category job. We used fashions like VGG19, Mobile Net and ResNet50 which are used for multi elegance category.**

***Index Terms*— VGG19, MobileNet, ResNet50, CNN.**

I. Introduction

Kidney stone disease (KSD), a common condition, is mostly caused by solid mineral deposition within the kidney. Depending on sociodemographic, lifestyle, nutritional, genetic, gender, age, environmental, and climatic factors, the frequency of the disease varies, but it has been progressively increasing in size. the world. KSD (kidney stone disease) has a high rate of Within years of the stone removal, around 11%. These stones are made of solid Mineral deposits which might be either found free in the renal calyces and pelvis or attached to the renal papillae. When the urine is oversaturated with a particular mineral, such as calcium oxalate, kidney stones can form. They are made up of crystalline and organic components. With rates up to 14.8%, stone formation is becoming more frequent, and after five years of the initial episode, recurrence rates might reach up to 50%. Obesity, diabetes, hypertension, and Metabolic syndrome are hazard elements for the development of stones. Hypertension, end-stage renal disease, and chronic kidney disease can all be brought on by stone development. People of color are more prone to get kidney tumors than any other type of cancer.

Diagnosis of disease in the kidney the task is challenging because of the problem it poses. kidney's intricate structure. To enhance the More efficient models and processes that can help in making accurate decisions needed to enhance the improve the precision of radiologists' diagnoses. process of identifying kidney stone disease. is based on multiple imaging modalities. This necessitates the ability of radiologists to interpret and provide a detailed diagnosis. Computer-aided diagnostic technologies can be helpful supplements to help clinicians with their diagnosis. In recent years, there have number of studies in which diseases have been diagnosed using deep learning. Besides deep learning, other features Computer vision encompasses various tasks, such as image classification and image recognition attribute extraction, and image classification by predicting future outcomes.

In the figure 1 the block diagram involves the collection of kidney CT scan images. This requires gathering a dataset that includes a different kind of images representing different conditions such as cysts, tumors, kidney stones, and normal kidneys. The dataset should be comprehensive and diverse to ensure accurate analysis and classification. Once the images are collected, the further step is image processing. This involves applying various techniques to improve the quality of the images and remove any noise or artifacts that may affect the

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subsequent analysis. Image processing methods may include noise reduction, contrast enhancement, and edge detection to improve the overall image clarity and make it suitable for feature extraction. After image processing, the block diagram involves the task involves extracting features using three distinct convolutional neural networks. (CNNs): VGG19, ResNet50, and Mobile Net. These CNNs are pre-existing models that have been trained on large-scale image datasets and have learned to extract meaningful features from images. By feeding the processed kidney CT scan images into these models, relevant features specific to each image can be extracted. subsequently is the classification of the extracted features. These features are utilized as input for a classifier that is trained to differentiate between different kidney conditions: cysts, tumors, kidney stones, and normal kidneys.

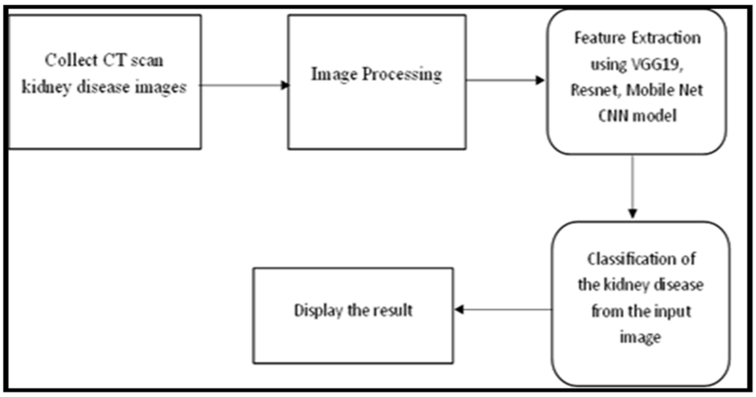

Figure 1. Block diagram of kidney disease classification

The classifier utilizes machine learning algorithms, such as support vector machines (SVM) or random forests, to learn patterns and make accurate predictions based on the extracted features. Finally, the block diagram includes the display of the disease classification results. Once the input image is processed, and features are derived and classified, the system can provide the predicted disease label for the kidney CT scan image. The output can be displayed to the user, indicating whether the image represents a cyst, tumor, kidney stone, or a normal kidney. This knowledge can benefit healthcare. professionals in diagnosing and treating kidney-related conditions more effectively.

II. RELATED WORK

Vishnu Prasad G. P, Kura Pati Vishnu Sai Reddy, proposed the new method for kidney stone detection 2021. Kidney stones are a prevalent disease all over the world, resulting in many of us being rushed to the hospital in excruciating pain. Calculus illness is diagnosed using a variety of imaging modalities [1]. Jyothirmai Joshi, Sai Nikita, Viswa Chandrika, Sindhu, Jahnavi proposed the system Kidney stones detection using Image processing technique. The main objective of this project is to detect the kidney stone from the digital ultrasound image of the kidney by performing various image processing techniques [2]. Kristian M. Black, Hei Law†, Ali proposed the new method Deep learning computer vision algorithm for detecting kidney stone composition. in the year 2021 [3]. Venkatasubramani. K, Chaitanya Nagu, Karthik proposed a system of Kidney Stone Detection Using Image Processing and Neural Networks in the year 2021. In the study, deep learning and backpropagation neural networks were employed. The kidney images in the collection were gathered from patients at various hospitals [4]. Krishnamoorthy Somasundaram1, Suresh Manimekalai, Paulraj Sivakumar proposed new method An Efficient Detection of Kidney Stone Based on HDVS Deep Learning Approach in the year 2021[5].

The identification of kidney stones utilizing CT scans and in-depth image processing techniques. The enhanced method to identify boundaries, segmented areas, and improve stone placement identification from the kidney was investigated in this study. This inquiry was useful in locating a stone based on pixels. The analysis revealed that this research has 92.5% accuracy using a reliable stone detection method [6]. A 2D-CNN version become proposed in which had 3 fashions regarding with Kidney Tumor detection together with a 2D convolutional neural community with six layers (CNN-6), a ResNet50 with 50 layers, and a VGG16 with sixteen layers. The closing version was used for type as a 2D convolutional neural community with 4 layers (CNN-4) [7]. A segmentation primarily based totally kidney tumor type the usage of Deep Neural Network (DNN) became used in. It had steps. Firstly, the kidneys have been segmented the usage of a guide segmentation method and educated U Net together with Seg Net for kidney segmentation [8]. Ghalib et al.carried out a observe for renal tumor detection the usage of deep studying techniques on CT scans. The authors evolved a green set of rules to come across and similarly examine renal most cancers tumors the usage of CT for patients. The preprocessing method concerned figuring out the noises of a CT test and getting rid of them with a right filtering method [9]. Liu et al. performed a observe for exophytic renal tumor detection thru system studying strategies on CT scans. They used 167 CT scans and evolved a framework for kidney segmentation on non-settlement CT pics the use of green perception propagation [10].

Budak [11], 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 and without 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 [11]. Feature extraction was based on nineteen gray level co-occurrence matrix (GLCM) features and five intensity histogram features P. Gladis Pushpa Rathi, V &Palani, S. (2011) proposed a method for segmenting the human brain for tumor detection. Image segmentation is done using Hierarchical Self Organizing Map (HSOM). Abnormal spectra and type of abnormality were determined using Artificial Neural Network and Wavelet packets [12]. Rahman, Tanzila& Uddin, Mohammad (2013) has reduced speckle noise using gabor filter and the image enhancement is done using the histogram equalization. Two segmentation techniques were used, cell segmentation and region based segmentation to extract the kidney regions [1]. Hafizah, Wan &Supriyanto, Eko & Yunus, Jasmy (2012) classified kidney ultrasound images into different groups creating a database based on the features extracted [13]. Bommanna Raja, K &Muthusamy, Madheswaran & Thyagarajah, K. (2007) identified significant content descriptive feature parameters and classified the kidney disorders with ultrasound scan Stevenson, Maryhelen& Winter, Rodney &Windrow, Bernard made an analysis to determine the sensitivity of feedforward neural network to weight errors [14]. In the paper by AV Gregory and DA Anaam (2021) reconstructed the goal of detecting or locating object and the segmentation job which is instance-based into a problem (semantic segmentation), and created the initially 3rd dimension semantic instance cyst segmentation method in MR images for kidney. Using a 3rd dimension watershed method on a 3D Euclidean distance map of generated cyst segmentation from the MRI pictures, from the manual cyst tracings they have built an initial instance of cyst segmentation. One label cyst segmentation was performed using a previously established automated semantic cyst segmentation technique to speed up the cyst segmentation procedure for the validation and training sets. The 3rd dimension watershed procedure explained in the prior section was applied to that resulting segmentation. They employed the U-Net architecture and four-fold cross-validation sets for the training and validation phases [15].

III. METHODOLOGY

The goal of the "Kidney Disease Classification" (KDC) project is to create a classification or a distinguishing system between kidney stones, kidney cysts, kidney tumors, and normal kidney conditions. The KDC model or algorithm is designed to analyze medical information, such as CT images or patient records, to classify the kidney condition based on the information provided. The aim of the project is to achieve high-quality classification to help healthcare professionals diagnose and treat kidney diseases more efficiently. Early detection of kidney diseases can result in early interventions, better patient outcomes and potentially lower healthcare costs.

In this project, we are proposing to use deep learning to classify the medical images as kidney stones, cyst, tumors, normal tissue, etc. The methodology is as follows:

1. Collect the dataset from Kaggle to ensure that the images are accurately annotated with the appropriate label.
2. Select the appropriate model architectures for the classification task, namely VGG19, ResNet50, MobileNet
3. Obtain the features from the medical images dataset by running the images through the selected pretrained models and extracting the output probabilities of each class.
4. Assess the effectiveness of the performance of the pretrained models on a specific validation dataset to measure their accuracy.

A. Dataset

The dataset for kidney disease classification consists of four classes cyst, tumor, stone, and normal kidney. The dataset is split into two folders: train and test. In the train folder, four classes exist, and representing a different

type of kidney condition. The cyst class contains 2919 images, the tumor class contains 4057 images, the stone class contains 1091 images, and the normal kidney class contains 2913 images. These images are representative of the respective kidney conditions, and they are employed to instruct the classification model.
Similarly, in the test folder, there are also four classes. The cyst class contains 780 images, the normal kidney class contains 1020 images, the stone class contains 280 images, and the tumour class contains 460 images. These visuals are utilized to assess the effectiveness of the trained model on unseen data. The cyst class represents images of kidneys with cysts, which are fluid-filled sacs that can form on the kidney. The tumour class represents images of kidneys with tumours, which are abnormal growths of cells. The stone class contains images of kidneys with stones, which are hard deposits that can form in the kidneys. Finally, the normal kidney class contains images of healthy kidneys without any abnormalities. The dataset provides a diverse set of images representing different kidney conditions, allowing for the development and evaluation of a classification model. This dataset can be used to train a machine learning model to classify kidney images into one of the four classes, enabling the automated detection and diagnosis of kidney diseases.

Figure 2. sample dataset

B.Model Description

There are many deep gaining knowledge of fashions "which may be replaced by an alternative word." handy at present. CNN are computational fashions made from interconnected neurons organized in layers and are stimulated through the human brain. Data is taken through the enter layer and propagated thru the hidden layers the usage of weighted connections. Neurons introduce non-linearities through making use of activation capabilities to the weighted sum of inputs. Up till the output layer starts off evolved to provide predictions, this ahead propagation procedure is continued. Mobile Net, VGG19 and ResNet50 are taken into consideration to the sub components of CNN.

1. MobileNetV2

The counseled community layout for class is visible in Figure. It includes a contracting course at the left and a classifier head at the right. By time and again making use of 3x3 convolutions every observed with the aid of using a linear unit of rectified form (ReLU), and a maximum pooling operation (2x2 max) with a stride of 2 for down. sampling, the contracting path adheres to the usual layout of a neural community. Repeating those 3 processing steps time and again creates a group of absolutely connected layers, known as Blocks. The function map matrix is flattened into vector shape at the realization of the MobileNetV2 level and fed into the classifier level, that's a completely related layer that resembles a neural community

2. ResNet

ResNet50 is a CNN community version that has revolutionized the sphere of pc vision. It includes 50 layers and is thought for its deep architecture, which enables triumph over the vanishing gradient problem. ResNet50 makes use of pass connections or shortcut connections to permit the go with the drift of facts from in advance layers to next layers, taking into account the advent of a deeper community without sacrificing performance. By addressing the problem of facts degradation at some stage in training, ResNet50 achieves super accuracy in responsibilities which includes photo classification, item detection, and photo segmentation.

3. VGG19

VGG19 (Visual Geometry Group) CNN (NGN) model that has become popular in the computer vision community. Named after the Oxford Visual Geometry Group, where it was first developed, VGG19 has a deep architecture consisting of 19 layers. This deep architecture helps VGG19 to extract complex features from images. VGG19 follows a simple and homogeneous design. It consists of multiple stacked convolution layers, each with small filter sizes. The convolution layers are then max-pooled to provide spatial down sampling. Because of its deep layers, VGG19 achieves high the performance in different visual recognition tasks, such as image-related tasks, is assessed. classification, and object localization.

IV. Implementation

The implementation of a kidney disease project involves the practical steps taken to address the challenges of kidney disease, such as prevention, early detection, diagnosis, treatment, and management. It begins with project planning, including needs assessment and stakeholder engagement, continued by the design of evidence-based interventions. Resources are allocated, training is provided to stakeholders, and continuous monitoring and evaluation are conducted. Collaboration and sustainability planning are key components to ensure long-term impact. By following this systematic approach, the project aims to alleviate the burden of, kidney disease and improve outcomes for affected individuals.

In the figure 3 the user interface provides a user-friendly platform that allows users to explore and select CT scan images in JPG or PNG format from their local file system. Users can locate the desired images and choose them for uploading to the system. Once the user has selected the JPG or PNG images, they can initiate the upload process by clicking on the "Upload" or "Submit" button. The system then transfers the selected image files from the user's device to the server hosting the project.

In the figure 3, the upload page is designed to make it easier to process of browsing and uploading image files for analysis and classification. This page serves as a user interface where individuals involved in the project can convey information to the system connect information to the system submit relevant image data. The page typically includes a file browse button or an option to choose a. folder, enabling users to navigate through their local file system or network storage. By clicking on this button, the file explorer window will open, allowing you to the user to search and select the desired image file or folder containing multiple image files related to kidney disease.

The result page of a kidney disease classification project provides information about the classification of different types of kidney conditions based on CT scan images. The goal of project is to accurately identify and classify the occurrence of tumors, cysts, stones, or a normal kidney in the given CT scan image with accuracy and visualization.

Figure 3. Screenshots of the GUI for Kidney disease classification

V. Results

In the table I below, we have three deep learning models were trained (VGG19), Mobile Net and ResNet on a dataset using the 80-20 split 80% models were trained using the dataset. 20% the data were utilised to test and evaluate the models' performance First, let's look at VGG19 It was instructed on 80% dataset and when we tested it on the remaining 20% dataset, it achieved 95% accuracy. VGG19 is a deep learning (DNN) architecture that is well-known for its depth and its ability to classify unseen images. The 95% accuracy indicates that the VGG19 was able to learn and generalize a set of practise data to classify unseen images accurately in the testing phase. The next move was to train the MobileNet model on the same 80% dataset. The MobileNet model was evaluated on 20% testing data and achieved an impressive 98% accuracy. MobileNet is a lightweight, convolutional neural net architecture that is optimized for efficient computing on mobile devices and embedded devices. The 98% accuracy suggests that the MobileNet model learns and generalized the patterns in the training data. This makes the MobileNet model highly accurate when classifying unseen images in testing. The ResNet model was also trained on 80% of the training data. The ResNet model achieved an impressive 93% accuracy when tested on 20% of testing data. The 93% accuracy indicates that ResNet learned and classified images with high accuracy, including previously unseen data in testing.

TABLE I. ACCURACY RATES FOR TRAINING AND TEST DATASET SPLIT OF 80-20

Dataset	Model	Accuracy
80-20	VGG19	95%
80-20	Mobile Net	98%
80-20	Resnet	93%

TABLE II. ACCURACY RATES FOR MODELS

Dataset	Model	Epoch	Accuracy
80-20	VGG19	10	74%
70-30	VGG19	10	69%
50-50	MobileNet	10	70%

TABLE III. ACCURACY RATES FOR MODELS

Dataset	Model	Epoch	Accuracy
70-30	VGG19	10	74%
70-30	VGG19	5	69%
70-30	Mobile Net	15	72%

Table II shows that VGG19Model achieves 74% accuracy when train and test are split in 80-20 ratio and the epoch is set to 10. Similarly, VGG19model achieves 68% accuracy for the 70-30 ratio. We repeated the experiment for mobile Net using the following parameters:70% accuracy for Mobile Net

In Table III, VGG19Model achieves 74% accuracy when train and test are split 70-30, and the epoch is set to 10. Similarly, the experiment is repeated for other models with the epoch set to 5. For VGG19 model, the accuracy is 69% and for Mobile Net, the accuracy is 73% when set to 15. The classification process involved three models: ResNet50, Mobile Net, and VGG19, which were used to classify different classes of kidney conditions. The classes included tumor, kidney stone, cyst, and normal kidney. Each model was evaluated to assess its performance in accurately classifying these classes. The graph can be created to visually represent the accuracies of the models, allowing for a clear comparison and aiding in the selection of the most reliable model for classifying tumor, kidney stone, cyst, and normal kidney conditions.

Figure 9 is graph obtained by vgg19 model. VGG19 is a complex CNN structure renowned for it is a complex CNN structure renowned for its simplicity and uniformity, comprising 19 layers. The accuracy graph for VGG19 typically exhibits a smooth increase in accuracy with training iterations or epochs. VGG19 tends to converge relatively slower compared to more modern architectures like ResNet-50 and Mobile Net. The accuracy graph may show a gradual and steady rise, with fluctuations decreasing over time. VGG19 can achieve great precision however often requires more computational resources and training time due to its deeper architecture. It's noteworthy is the fact that the specific accuracy graphs for these models may differ based on the dataset, training parameters, and implementation details. The broad patterns discussed here offer a typical overview of how the accuracy of these models may evolve during training.

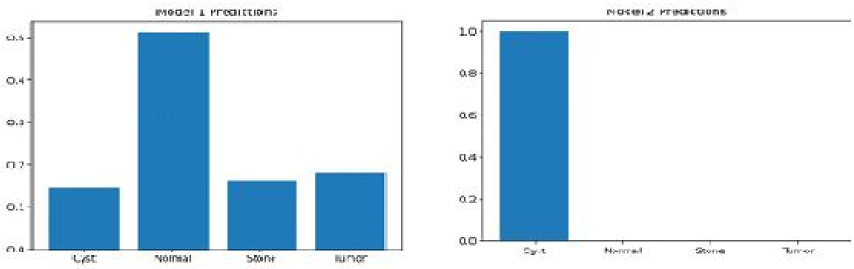

Figure 4. VGG19 and ResNet model classification

The given figure 4 is graph obtained by resnet 50 .ResNet-50 is an advanced convolutional neural network (CNN)architecture renowned for its incorporation of residual connections, which revolutionized the training of extremely deep networks. When looking at the accuracy graph of ResNet-50, it becomes apparent that it illustrates the correlation between the number of training iterations or epochs and the accuracy attained by the model on a validation or test dataset.Initially, during the early stages of training, the accuracy graph for ResNet-50 exhibits a notable and rapid ascent. This early surge signifies the model's ability to swiftly grasp low-level features from the input images, showcasing its effectiveness in capturing basic visual patterns. As the training progresses, the rate of accuracy improvement tends to decelerate. However, the model perseveres and continues to learn more intricate and complex features, leading to a gradual climb in accuracy.Throughout the training process, the accuracy graph may display occasional fluctuations or plateaus, indicative of the model's convergence. These fluctuations can be attributed to various factors, including theinherent complexity of the dataset or the presence of outliers. Despite these fluctuations, ResNet-50 consistently demonstrates remarkable accuracy, frequently surpassing the performance of previous state-of-the-art models in various computer vision tasks.

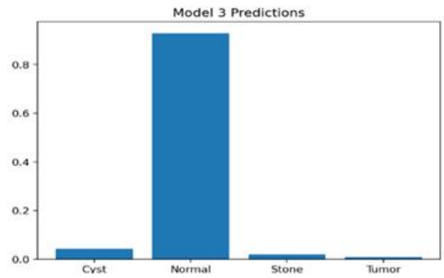

Figure 5. MobileNet model classification

In the given figure 5 graph obtained from mobilenet model. mobilenet is an artificial neural network design that was created especially forthe purpose of mobile and resource-constrained devices. Its primary advantage lies in its efficiency and suitability for deployment on What is a device with a limited amount of computing power, such as smartphones or embedded systems. The accuracy graph of Mobile Net generally follows a similar pattern to that of ResNet-50, a larger and more complex model. However, there are a few distinctions between them due to Mobile Net’s smaller size and reduced computational requirements. Initially, when Mobile Net is compared to ResNet-50, it may exhibit lower accuracy.

This is primarily because Mobile Net has a minimizing number of parameters and a reduced model capacity. It may struggle to capture complex features and the data as patterns effectively as ResNet-50. However, as Mobile Net undergoes training, its accuracy steadily increases. This increase in accuracy demonstrates that Mobile Net is capable of learning meaningful representations and achieving competitive performance levels. Despite its lightweight design, Mobile Net can still capture important features and patterns in the data, enabling it to make accurate predictions.

VI. CONCLUSIONS

In conclusion, the kidney stone, cyst, tumor, and normal kidney classification project aimed to analyze and categorize medical data related to kidney health. The dataset contained 12,446 unique samples, with the cyst category comprising 3,709 samples, the normal category containing 5,077 samples, the stone category consisting of 1,377 samples, and the tumor category including 2,283 samples. The project's objective was to develop a classification model capable of accurately identifying and distinguishing between these four kidney conditions. By leveraging machine learning algorithms and techniques, such as deep learning or decision trees, the project aimed to Provide medical professionals with a valuable resource. to aid in diagnosing and treating kidney-related conditions. The successful implementation of such a classification model would Carry considerable consequences for improving patient care, treatment planning, and overall kidney health management. 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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