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KIDNEY DISEASE DETECTION USING DEEP LEARNING MODEL

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Abstract: Kidney disease poses a significant health challenge, with kidney stones being a common manifestation that requires timely diagnosis and treatment. Traditional diagnostic methods often rely on radiological imaging, which can be time-consuming and subjective, heavily reliant on the expertise of radiologists. This research introduces a novel approach to automate the detection of kidney stones using deep learning techniques.

In this study, a diverse dataset of medical images, encompassing normal kidney tissue, kidney stones, cysts, and tumors, is collected and annotated. Two state-of-the-art deep learning architectures, VGG16 and ResNet50, are employed for the classification task, leveraging their ability to extract intricate details from medical images.

The methodology involves data preprocessing, including dataset balancing to prevent class imbalance bias. Feature selection techniques are applied to improve classification accuracy by removing irrelevant and redundant attributes. Convolutional Neural Networks (CNNs) are utilized, comprising convolution, pooling, and fully connected layers, to identify patterns in the images and classify them into the relevant categories.

Results demonstrate the efficacy of the proposed deep learning models, achieving an impressive accuracy rate of 99.36% in the classification of kidney stones, cysts, tumors, and normal kidney tissue. Confusion matrix analysis further validates the model's accuracy.

The outcomes of this research indicate that deep learning models can significantly expedite the diagnostic process for kidney disease, reduce healthcare costs, and potentially lead to earlier diagnoses and treatments. Moreover, the burden on radiologists can be alleviated through the deployment of a fully developed automated system for kidney illness detection.

Keywords: -Kidney Disease, CNN, Machine Learning, Image Processing, Deep learning

I. INTRODUCTION

Kidney disease (KSD), a common disease, is mostly caused by solid mineral accumulation 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 steadily rising over the world. A high 11% recurrence rate of kidney disease (KSD) is observed within two years of the stone removal. These stones are made of solid mineral deposits that are either found free in the renal calyces and pelvis or attached to the renal papillae. Kidney stones can develop when the urine contains an excessive amount of a certain mineral, such as calcium oxalate. They contain both organic and crystalline elements. Stone formation is becoming increasingly common, with rates up to 14.8%, and five years after the initial episode, recurrence rates may reach up to 50%. Stones can form as a result of obesity, diabetes, hypertension, and the metabolic syndrome. Stone formation can result in hypertension, chronic kidney disease, and end-stage renal disease. People who are older are more prone to acquire kidney tumors than other types of cancer. Kidney cysts, also known as renal cysts, are round or oval pockets of fluid in the kidneys.

The interest in digital biomedical image processing techniques currently occupies a very significant position in two major and significant fields. The most crucial one is the processing of biomedical picture data for storage and the enhancement of visual information for human investigations. Sometimes, a biological image is described as a two-dimensional function, (x,y), where x and y represent the value or gray level of the image at a particular location. they're all discrete, finite quantities. We should be aware that when a picture is made up of a limited number of elements, each of which has a specific position and value, the image is said to be a digital image. According to experts at the University at Buffalo School of Medicine and Biomedical Sciences, the setting time for an MRI image with a gray level is depicted in figure as an example. They have published the MRI findings of patients who received a multiple sclerosis diagnosis as children. The biological image's differences are not limited to its area but also its mCNN processing. Due to the varied anatomy of the kidney, illness detection might be difficult. There is a need for more effective models and procedures that can aid in making accurate decisions in order to increase the accuracy of radiologists' diagnoses. Several imaging modalities are used in the diagnosis of Kideny illness, and their interpretation and comprehensive diagnosis necessitate the skills of professionals. Computer aided diagnosis systems can act as helpful auxiliary tools to assist clinicians in their diagnosis.

II. LITERATURE SURVEY AND RELATED WORK

Level Set Segmentation:

In order to identify kidney problems such, the formation of stones, cysts, blocked urine, congenital deformities, and malignant cells, K. Viswanath and Dr. R. Gunasundari employed level set segmentation in 2015. It is crucial to identify the kidney stone's actual and exact location during surgical procedures. Since kidney stones have low contrast and speckle noise, finding them via ultrasound imaging is a very difficult task. The solution to this problem is to use the right image processing methods. Using the image restoration procedure, the ultrasound image is first preprocessed to remove speckle noise. Histogram equalization is used to improve the image after the restored image has been smoothened using the Gabor filter. Level set segmentation is used to detect the stone region in the preprocessed image. To achieve better outcomes, the segmentation procedure is used twice: once to segment the kidney section and once to segment the stone portion. In this study, momentum and resilient propagation (R prop), two words used in level set segmentation, are used to identify the stone section. After segmentation, energy levels are derived from the kidney stone's extracted region using wavelet sub bands from the Smelts, Biorthogonal (bio3.7, bio3.9, and bio4.4), and Daubechies lifting scheme. By comparing these energy levels to those of normal energy levels, they show that stones are present. They have been taught to classify and identify the type of stone with an accuracy of 98.8% using multilayer perceptron (MLP) and back propagation (BP) ANN. The proposed work is created

Seeded region growing based segmentation:

P.R. Tamilselvi and P.Thangaraj (2011) presented a method for segmenting and classifying kidney images with stone sizes in order to diagnose stones in ultrasound renal images and to detect them early. The intensity threshold fluctuation in segmented regions of the images aids in the identification of multiple classes to categorize the images as normal, stone, and early stone stages. The image granularity features determine the homogenous region of the improved semiautomatic Seeded Region Growing (SRG) based image segmentation algorithm, where the retrieved structures with dimensions similar to the speckle size are of interest. The lookup table entries determine the growing regions' size and shape. The high frequency artifacts are also suppressed by the region merging that occurs after the region increasing. Based on the intensity threshold fluctuation found in the segmented regions of the picture and the comparison of the segment sizes to the standard stone sizes (less than 2 mm absence of stone, 2-4 mm early stages, and 5 mm and above existence of kidney stones), the diagnosis is made. Results: Using a variety of ultrasound kidney image samples obtained from the clinical laboratory, the parameters of texture values, intensity threshold variation, and stone sizes are assessed. In contrast to prior studies, the texture recovered from the segmented kidney pictures shown in our work accurately estimates the size of the stones and their location in the kidney.

III. IMPLEMENTATION STUDY

The current kidney stone detection technology uses level set segmentation and a smoothing Gabor filter. We saw a few difficulties as a result of using level set segmentation, such as the need to put a lot of care into building the right velocities for progressing the level set function. To obtain the accuracy rate, a large amount of data must be accessible, which is often not achievable.

PROPOSED WORK AND ALGORITHM

I have proposed a system that classifies kidney stones, cysts, tumors, and normal using deep learning and a pretrained model for the classification task. With the help of 12,446 images using the entire abdomen and the neurogram technique, a dataset titled "CT KIDNEY DATASET: Normal-Cyst- Tumor and Stone" has been compiled and annotated. The VGG16 and Resnet50 CNN-based deep learning models, which employ a transfer learning approach, are used to identify kidney problems, and their performance has been well studied.

1) Data collection: The photos in the dataset are labeled as kidney stones, cysts, tumors, or normal tissue after being downloaded from Kaggle.

2) Model selection: Picking an architecture for a pretrained model that is suitable for the classification task. For classification, VGG16 and ResNet50 have been selected. The pretrained model need to be able to extract intricate details from medical photos.

The features from the dataset of medical photos can be extracted using a pretrained model in step three, "Feature Extraction." In order to do this, images must be fed into the pretrained model in order to determine the output probabilities for each class.

4) Model evaluation: Assess the correctness of the pretrained models using a separate validation dataset.

5) Comparison and Analysis: Which model performs better for the given job is determined by the CNN model's performance. To determine the strengths and weaknesses of the model, the outcomes are analyzed.

IV. METHODOLOGY

DATASET

This study makes use of a set of MRI scans from Kaggle that was provided by Revolution Analytics for the diagnosis of kidney illness.

DATA PREPROCESSING

Data preprocessing is done prior to feature selection for the classification algorithm's efficient implementation. To balance the dataset and prevent the classification algorithm from favoring the dominant class, under-sampling is used. A balanced dataset is used to implement feature selection.

FEATURE SELECTION

The accuracy of a prediction model can be increased or decreased by removing superfluous, irrelevant, and redundant attributes from a dataset. These attributes are removed using feature selection methods. Seven feature selection methods, including Select-K-best, Feature Importance, Extra-Tree classifier

IMPORTANCE OF A FEATURE

Indicating the relative importance of each feature at the time of producing a prediction, feature importance is a set of strategies for giving scores to input features in a predictive model. The quantity of input features is decreased.

ALGORITHM

Convolutional Neural Networks (CNN, or ConvNet) are a type of multi-layer neural network that is meant to discern visual patterns from pixel images. In CNN, 'convolution' is referred to as the mathematical function. It's a type of linear operation in which you can multiply two functions to create a third function that expresses how one function's shape can be changed by the other. In simple terms, two images that are represented in the form of two matrices, are multiplied to provide an output that is used to extract information from the image. CNN is similar to other neural networks, but because they use a sequence of convolutional layers, they add a layer of complexity to the equation. CNN cannot function without convolutional layers. CNN artificial neural networks have excelled in a range of computer vision tasks. Convolutional neural networks have many layers, including convolution layers, pooling layers, and fully connected layers. They use a backpropagation method to automatically and adaptively learn spatial hierarchies of input. In the section that follows, you can find further information about these terms.

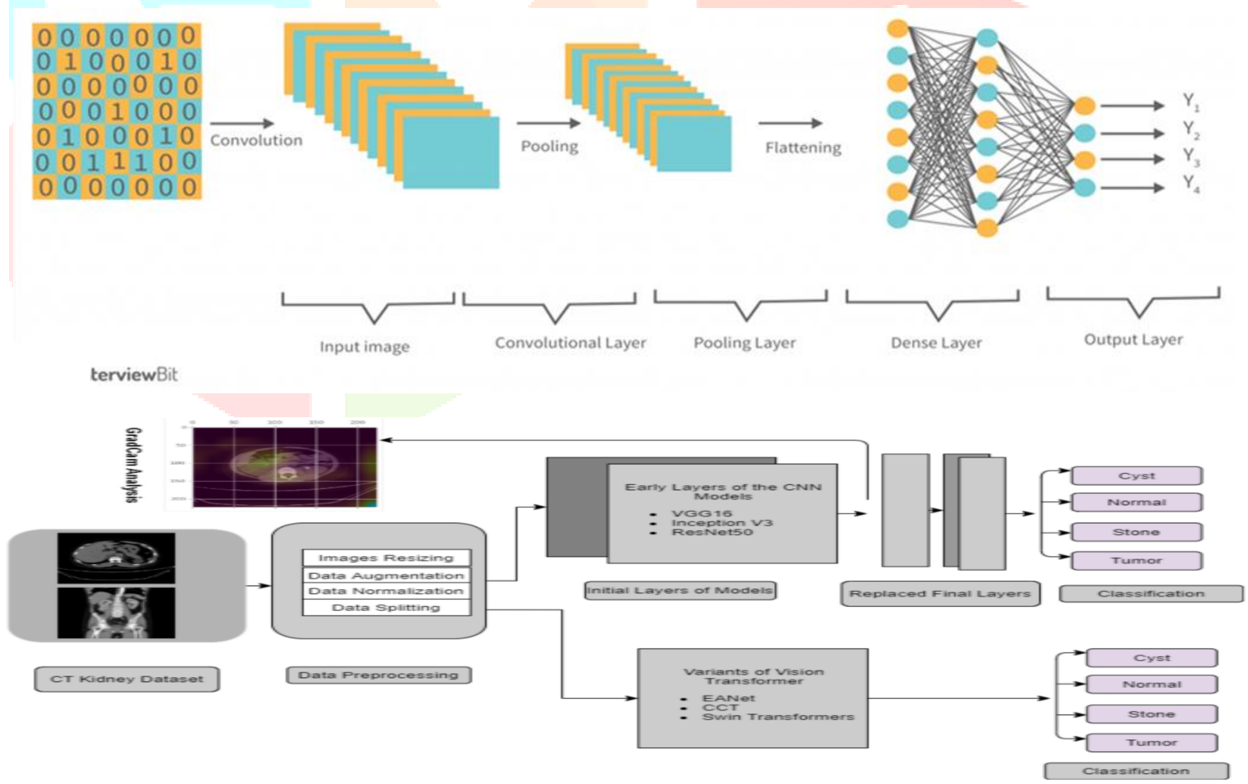

Fig 1:- proposed CNN Model

Convolutional Layer (CONV):

This layer serves as the backbone of CNN and is responsible for carrying out convolutional operations. The element in this layer that does the convolution operation (matrix) is the Kernel/Filter. The kernel makes horizontal and vertical changes based on the stride rate until the entire image is scanned. While the kernel is smaller than a picture, it is deeper. The kernel height and width will be modest in size if the image has three (RGB) channels, but the depth will cover all three. Convolutional layers also contain the Non-linear activation function, which is a significant component in addition to convolution. A non-linear activation function is applied to the outputs of linear processes like convolution.

Pooling Layer (POOL):

This layer, known as the Pooling Layer (POOL), is in charge of minimizing dimensionality. It helps to lessen how much computing power is needed to process the data. Maximum and average pooling are the two categories into which pooling can be classified. Max pooling returns the highest value from the kernel-covered region of the image. Average pooling gives the average of all the values in the area of the picture covered by the kernel.

Fully Connected Layer (FC): Each input is coupled to each neuron in the fully connected layer (FC), which operates with flattened inputs. The flattened vector is then transmitted via a few more FC layers, where the usual mathematical functional operations are carried out. . At this moment, the classification process begins. If FC layers are present, they are often located near the end of CNN architectures. A CNN architecture also includes several other terminology in addition to the layers mentioned above.

Activation Function: The activation function of the final fully connected layer is typically different from the others. The proper activation function must be chosen for each activity. The SoftMax function is an activation function used in the multiclass classification problem. It normalizes output real values from the last fully connected layer to target class probabilities, where each value ranges from 0 to 1 and all values add up to 1.

V.RESULTS

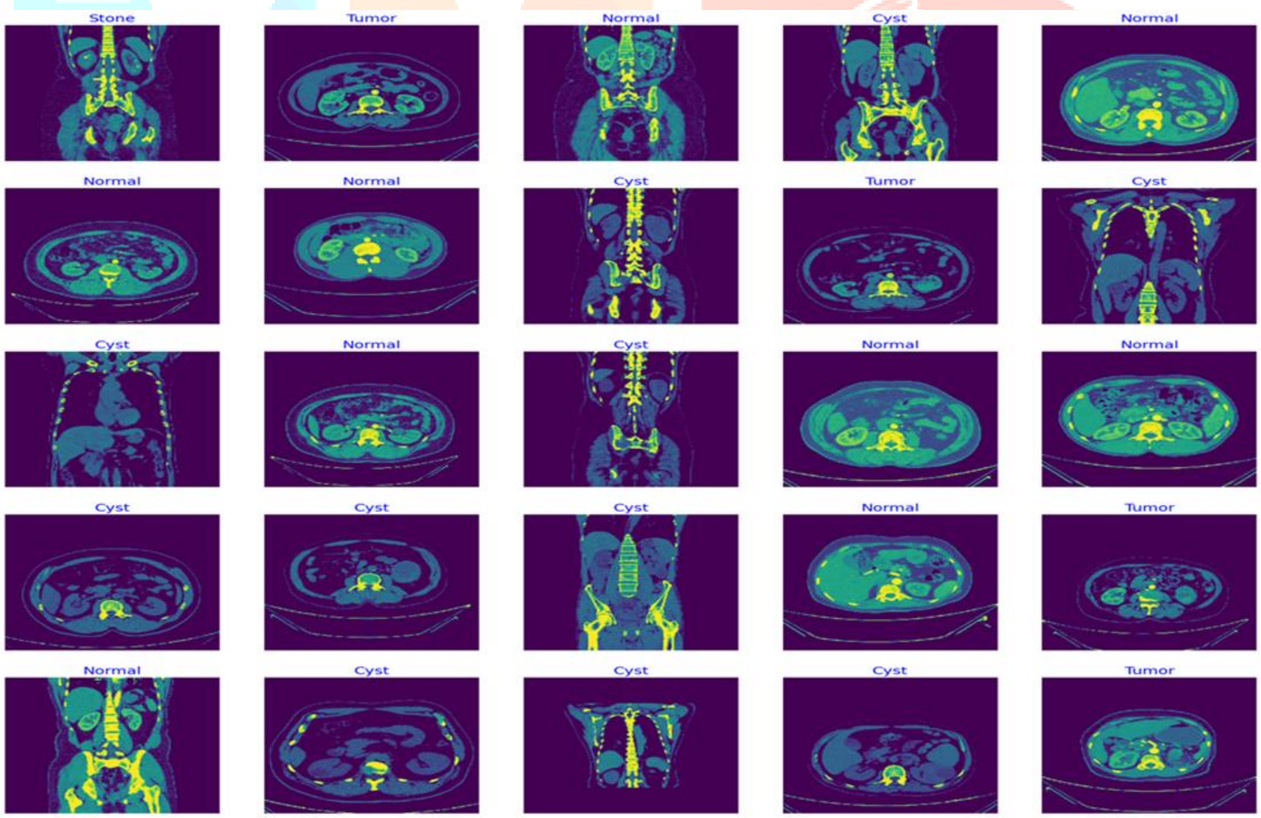

Fig 2: - Sample Images from Dataset

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 198, 198, 32)	320
max_pooling2d_6 (MaxPooling2D)	(None, 99, 99, 32)	0
conv2d_7 (Conv2D)	(None, 97, 97, 32)	9248
max_pooling2d_7 (MaxPooling2D)	(None, 48, 48, 32)	0
conv2d_8 (Conv2D)	(None, 46, 46, 64)	18496
max_pooling2d_8 (MaxPooling2D)	(None, 23, 23, 64)	0
conv2d_9 (Conv2D)	(None, 21, 21, 64)	36928
max_pooling2d_9 (MaxPooling2D)	(None, 10, 10, 64)	0
conv2d_10 (Conv2D)	(None, 8, 8, 128)	73856
max_pooling2d_10 (MaxPooling2D)	(None, 4, 4, 128)	0
conv2d_11 (Conv2D)	(None, 2, 2, 128)	147584
max_pooling2d_11 (MaxPooling2D)	(None, 1, 1, 128)	0
flatten_1 (Flatten)	(None, 128)	0
dense_2 (Dense)	(None, 512)	66048
dense_3 (Dense)	(None, 4)	2052

Total params: 354,532

Fig 3: - Total Trainable Parameters

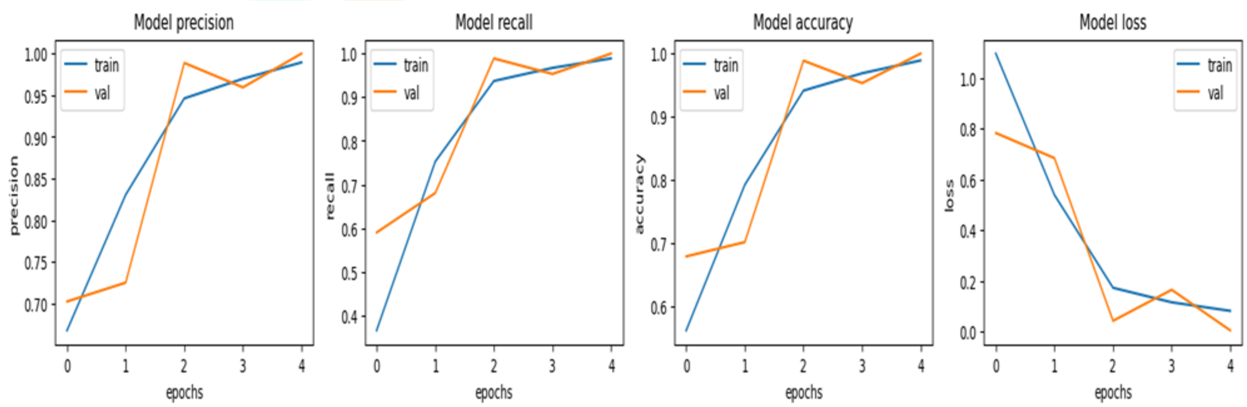

Fig 4 :- Model Accuracy And Evaluation Metrics Graph Accuracy Archived 99%

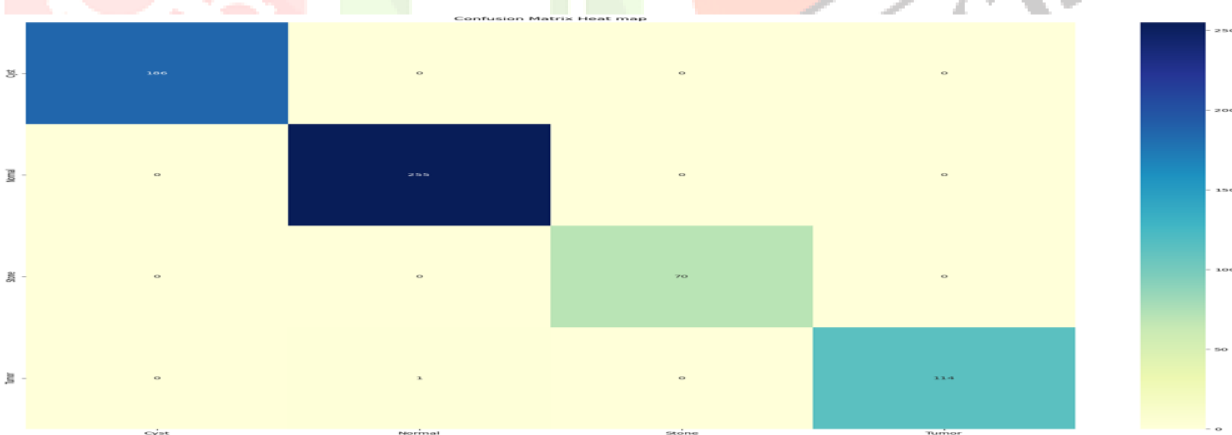

Fig 5 :-Confusion Matrix Of The Predicted Labels Hence The Model Was Trained With An Accuracy Of 99.36%

VI. CONCLUSION AND FUTURE SCOPE

This strategy has the potential to cut down on the time it takes to get findings and the expense of diagnostics, and it can lead to early diagnosis and fast care. The duty of radiologists can be decreased with the use of a fully developed system for detecting kidney illness.

THE FUTURE SCOPE

Experimentation reveals that the suggested method requires a sizable training dataset for more accurate results; in the field of medical image processing, collecting medical data is a laborious task, and in certain rare instances, the datasets could not be available. In each of these scenarios, the suggested algorithm must be trustworthy enough to reliably identify tumor locations from MR images. The suggested method can be further improved by working with weakly trained algorithms that can detect irregularities with little or no training data. Self-learning algorithms would also help to improve algorithm accuracy and speed up processing.

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