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Deep Learning Model for Automated Kidney Stone Detection using VGG16

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Abstract-Urine crystallization that results from chemical concentrations or a congenital tendency is known as kidney stone formation. The prevalence of kidney illnesses is rising worldwide, and the majority of those who have it are unaware they have it since it progressively deteriorates the organ before causing symptoms. Although they are frequently ignored until they cause agonizing stomach pain or have an odd urine color, kidney stones can also form in newborns. It is simpler to take action the earlier kidney stones are discovered. Various image processing phases are used in the methods described in this article to locate kidney stones. The first step in photo preparation is the use of filters. Through this process, noise is also removed as the image is smoothed. Following that, the pre-processed images are segmented using the guided active contour technique. The next stage is to use renal imaging data to diagnose illness using convolutional neural network technology. Since CT has less noise than other imaging modalities like X-ray and ultrasound, it is the favored imaging technique.

KEYWORDS-Kidney Stone, Features extraction, Deep learning, Medical images, Convolutional neural network.

I. INTRODUCTION

A crucial organ in the human body is the kidney. Today, kidney stones are a widespread issue. Minerals in urine cause kidney stones, which are solid bits of material. They are the outcome of a confluence of genetic and environmental variables. Other risk factors include eating particular foods, using certain drugs, drinking insufficient water, and being overweight. People of diverse ages, ethnic and cultural origins, and geographical locations can develop kidney stones. Imaging, blood, and urine testing are just a few of the methods used to diagnose this kidney stone. If the stone is not found right away, the problem might get worse and surgery to remove it might be necessary. The process of processing images may be used to locate stones quite precisely. The most crucial aspect of medicine is imaging. Clinicians can examine inside organs thanks to medical imaging. Doppler scans, CT scans, and ultrasonic scans all employ different scanning techniques. Due to the use of erroneous data, poor algorithms, etc., making a medical diagnosis can occasionally be very difficult and ambiguous. In the past, kidney stones in ultrasound pictures have also been recognized using a number of mathematical techniques. However, image processing offers the most benefit since it carefully examines the stones.

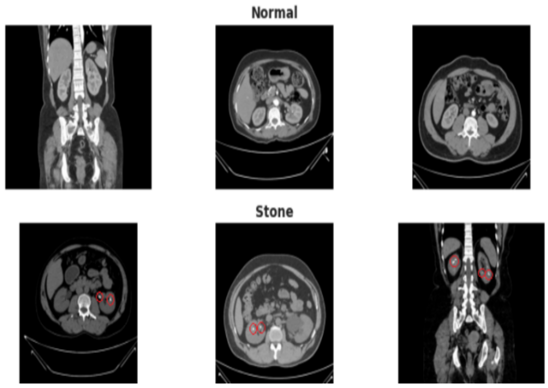

Fig 1: CT scan images of Kidney with Normal and Stone

One of the most popular, non-invasive, and cost-effective imaging modalities for diagnosing renal disease is ultrasound imaging. One of the most serious and potentially fatal illnesses in the world is kidney stone disease. The kidneys are affected when the stone disease advances and is missed in its early stages. Kidney failure is usually brought on by glomerulonephritis, diabetes, hypertension, and other illnesses. Early diagnosis is advised since renal failure might pose a concern. An inexpensive, non-invasive method of diagnosing renal disease is ultrasound (USA). This is one of the options that the present imaging technique under consideration provides.

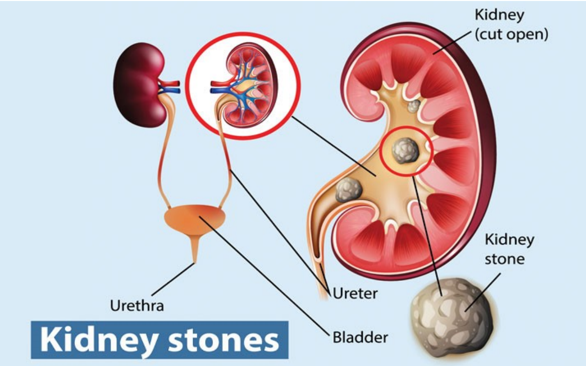

Fig 2: Kidney stones

II. RELATED WORKS

Abubaker Abdelrahman, among others [1] provides a method for segmenting the kidney and renal tumour by using thorough understanding and building blocks, in addition to cutting-edge tactics and execution tools. Existing methodologies let him achieve his dual goals of accurately segmenting tumours and addressing the knowledge gap in schooling. Using data from Pinnacle Education, DL can effectively segment kidney cancers. The ensemble technique, he's, and U-Net based models enhance the utilisation of the art with correct pre-processing, weight initialization, cutting-edge education schemes, segmentation through specific boundaries, and extraction of more data for pixel categorization. It's got great potential. The primary cause of many segmentation algorithms' terrible average overall performance is the absence of large medical education information devices. Geoff N's challenge of segmenting kidneys and renal malignancies has been met with extraordinary success and is a good place to start for future advancement. It has received many submissions and is still an important and worrisome standard for 3-D segmentation. However, it may be appropriate to extend the use of one's systems outside the research set's sample population. The accuracy of diagnostic algorithms can be increased by using additional imaging methods in addition to CT alone, such as MRI and contrast-enhanced ultrasound (CEUS).These systems were derived from multi-institutional cohorts that included individuals sharing the same geographic area, health care resource, and examination set.

Gianmarco Santini and others, et al. An automated method for semantic segmenting kidney and renal cancer tissue from higher contrast CT data is presented. In the context of treating renal tumours, particularly nephron-sparing surgery, which necessitates precise localisation of tissue to be removed, accurate evaluation of renal and renal tumour capacities is of the utmost importance. The need for accurate and automated sketching equipment is where the KITS19 mission began. By distributing a specialized dataset of 300 segmented CT scans, we hope to accelerate research and development in this area and facilitate analysis and treatment planning. To complete this objective, we proposed his autonomous, multi-degree deep learning-based 2.5D segmentation technique based solely on the ResUNet architecture.In order to combine forecast results from earlier ranges and reduce the variation across character styles, an ensemble operation is finally developed. Our neural community segmentation set of rules yields common Dice scores of 0. 96 for the kidney and 0. 74 for the kidney tumour on 90 unseen's, respectively. See instances. The findings are encouraging and might be improved by taking into consideration benign cysts' past information, which significantly improves tumour segmentation outcomes.

Jun-young A deep learning technique to renal parenchymal segmentation from CT images recorded in renal SPECT/CT investigations has been shown by Park et al. [3] to be a very accurate and automated estimate of GFR. According to CNN results, manual segmentation had a relatively high Dice coefficient (0.89), demonstrating a significant connection between manual and automatic approaches' %ID and GFR. Delineate her VOI automatically with just renal parenchyma, as if her CT intensities on non-enhanced CT images acquired with a SPECT/CT scan are quite comparable, and her VOI free of cysts or tumours. The VOI of an is difficult to describe. Despite this imprecision, the patient's GFR error was just 2.48 because the tumour's radioactivity was so low. He programmed his CNN to draw his VOI on both kidneys' renal parenchyma, but this resulted in a mistake in patients who only had one kidney. S6, CNN identified his extended VOI in the liver parenchyma of a patient lacking a right kidney (yellow arrow).

Fuat Turk and colleagues published a novel hybrid V-Net model that combines the greatest features of earlier V-Net models [4]. V-Net models with respective DSC rates of 0.865 and 0.977.This research demonstrates how organs and tumors may be successfully separated from computational pictures using V-Net models, suggesting that there may be room for improved V-Net models.Utilizing medical images, multi-organ segmentation models are improved. As a result of the ResNet++ design's favorable impact this study can serve as a reference for future hybrid models after the initial successful use of the hybrid V-Net model.The ResNet++ design is only sent to the output level, allowing segmentation data to be preserved.The fact that every parameter only works when it is supplied to the right block inside the model makes this situation potentially critical for model design. The findings reported here imply that more research into the hyperparameters of this version is necessary.

A quit-to-quit 3-D framework for precise automated segmentation of kidneys and renal cancers was proposed by [6], among others, Andrey Myronenko. Our team has a limited encoder/decoder structure that handles side records independently and is monitored by side reputation loss. By practicing and analyzing our approach using the MICCAI kits Kidney Tumour Segmentation Challenge 2019 dataset, we were able to demonstrate its efficacy. Our method consistently produced kidney and tumor die values of 0.9742 and 0.8103, and the total blended die cost was 0.8923. Here, we present a fully convolutional neural network (CNN) with a quit-to-quit interface for precisely segmenting kidneys and renal malignancies from arterial-segmented belly 3-D CT images..Incorporating an encoder-decoder structure that explicitly accounts for side records in organs and tumours by developing committed boundary bifurcations watched over by a side reputation loss condition is something we suggest the segmentation community to do.

Using a completely automated method, Luana Battista da Cruza et al. [7] showed renal segmentation of tumours on CT. Two conventional neural network models and post-processing techniques were used for this. Furthermore, image processing methods including histogram definition and normalization were used. The first conventional neural network model constructed on Alex Net was used for CT slice classification to reduce the scope of the problem. Cardioid tissue was properly partitioned using the second model, U-Net. Slice categorization, kidney segmentation, and post-processing methods to eliminate false positive results are ultimately combined to provide the results of the suggested approach.We make use of the extremely complicated and varied public database KiTS19 to validate the suggested strategy. The renal slice recovery phase was crucial in the suggested strategy even if some of the classification performance indicators could not be improved. This increased the kidney segmentation step's accuracy and enhanced the quality of the outcomes. This is made possible by the high sensitivity rate. We were able to provide the greatest kidney segmentation results utilizing a U-Net-based CNN by combining the aforementioned approaches.In overall, our technique offered promising findings, shown strong robustness in the face of such different and complicated databases, and stood out among the top efforts in the field. In light of these findings, we believe that the suggested technique, notwithstanding its limits, offers a significant contribution to the scientific environment.

Sabarinathan, among others, [8] The Hyper Vision Net architecture used in this study for the precise and automated segmentation of kidney and tumor areas was inspired by convolutional neural networks' superior performance.The KiTs19 dataset is used in the challenge. For certain categories of training and validation images, the effectiveness of our system is quantified statistically and statistically qualitatively. On the training set and validation set, our technique produced maximum cube values of 0.9633 and 0.9535, respectively. In terms of cube results, the suggested Hyper Vision Net demonstrated the best segmentation outcomes. The dataset, which KiTs19 contributed to for the proposed model's training and validation, comprises of 45964 actual 300 patient arterial-phase abdominal CT scans.The findings demonstrate that our method outperforms the most recent segmentation method, with training cube values for the cancer and kidney areas of 0.9552 and 0.9633, respectively.

To address the historical influence issue, Omid Bazgir et al. [9] inserted a derived MRI assessment method into the localization stage before the identified segmentation. Then, to reduce the variety of parameters, we modified the 3-D U-Net and added a cube loss characteristic for segmentation. Third, to increase the diversity of educational datasets, we combined augmentation and MRI histogram matching. We also used this method to our dataset's super-decision images to see whether the upgraded images should increase segmentation performance. These techniques had been tested using an animal model of lupus nephritis in preclinical MRI. Strategies for in vivo imaging offer advantages and disadvantages. Notably, his MRI uses no ionising radiation, is operator-independent, and does genuine tissue evaluation, which allows it to segment the kidneys and provide volume-related information. The local kidney was assessed using conventional methods. To deal with these problems, we advise sectioning the kidney using an integrated deep getting-to-know version rather than manual tracing, stereology, or general picture processing procedures since they may be laborious, time-consuming, or inconsistent.

Yuliia Kamkova et al. [10] created a brand-new mixed methodology for kidney and tumor segmentation.Our method, which combines 2D and 3D techniques, entails Deep She is learning kidney detection and segmentation techniques. We were able to get quick and effective cardioid identification results by combining Faster R-CNN with ResNet50. Additionally, this community developed a 3-d slice field that extracts the region of interest most effectively. These 3-d volumes are used with a V-Net, mostly to correctly segment kidneys and tumours. As part of the Kidney Tumour Segmentation Challenge, this study describes a method for automated kidney and tumour segmentation (KiTS19) The KiTS19 initiative released a dataset of 300 specific kidney cancer patients with guide annotation from Climb 4 Kidney Cancer (C4KC).Here,we proposed a cutting-edge combinatorial cascade deep learning (DL) approach to take on the difficult task. Deep learning-based segmentation was used after deep learning-based detection to identify kidneys that included tumours, allowing for domestic identification of both kidneys and tumours.

III. EXISTING SYSTEM

There are several existing systems for predicting hypothyroidism, a condition in which the thyroid gland does not produce enough hormones. The measurement of thyroid-stimulating hormone (TSH) levels in the blood is one widely used technique. The pituitary gland produces more TSH when the thyroid gland is not releasing enough hormones in an effort to encourage the thyroid to increase hormone production. Therefore, high TSH levels can indicate hypothyroidism. Another method is measurement of the levels of thyroxine (T4) and triiodothyronine (T3) in the blood. Low levels of these hormones can indicate hypothyroidism. Additionally, some doctors may also use imaging tests such as ultrasound or MRI to evaluate the size and function of the thyroid gland. However, it's important to note that these tests are not always conclusive and a final diagnosis may require additional testing and consultation with an endocrinologist.

Manual segmentation: detect the kidney regions by manual interventions.

Regions of interest (ROIs) with Machine learning: Kidney lesions are detected and classify whether it is lesions or not.

Intensity thresholding: The sole factor used to differentiate between voxels inside of objects and those in the background is image intensity.

1V. THE BACKGROUND OF WORK

For surgical planning and navigation in renal tumour ablation, kidney segmentation which is employed in stomach computed tomography (CT) sequences—is a critical job. From crude to excellent, it ranges. The tactic has been applied. These phases consist of: segmentation that is challenging and fun The SKFCM set of rules adds kernel properties and spatial constraints to the bushy C-approach clustering (FCM) set of rules. The FCM set of rules exploits the local CT sequences' continuity to automatically generate seed labels and enhance segmentation performance. The efficiency and sustainability of the suggested technique were demonstrated by experimental findings on the entire statistical set of CT images of the stomach. The kidney pictures also showed the necessity of right movement correction, which yields inaccurate and inconsistent findings. Since it lacks validity, scientific modelling cannot be used. His DCE-MRI kidney pictures from moving MRI kidneys are used in the proposed approach to improve accuracy and detect kidney disease. Using a set of component recognition criteria, edges are recovered from the MRI kidney images. Real-time input pictures of a moving kidney from an MRI have been used experimentally to assess existing systems. These images may be very useful for doctors to study in order to understand more about the prostate illness and associated therapies for their patients. Glomerular Filtration Rate, Segmentation, and Magnetic Resonance Imaging are used as keywords. The issue of registering moving human kidney images acquired with a DCE-MRI demands appropriate motion correction in addition to registration and segmentation. They demonstrate the efficacy of our segmentation-driven registration strategy for the entire pharmacokinetic glomerular filtration rate (GFR) model-driven segmentation of the kidney in medical imaging.

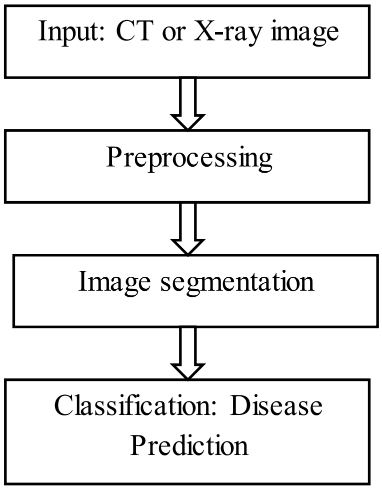

Fig 3: Existing block diagram

V. PROPOSED METHODLOGY

By analysing a data set produced from a scanned picture, deep learning technology assists in the categorization of renal disease patients. The objective is to automate this procedure in order to quickly and accurately diagnose renal illness using deep learning techniques. Segment the kidney lesion spot using the Guided Active Contour method. Additionally, a VGG16 framework is applied to identify the pictures more accurately. The recommended approach also lowers the frequency of false positives. VGGNet, CNN, was developed in collaboration between the Visual Geometry Group at the University of Oxford and Google DeepMind.

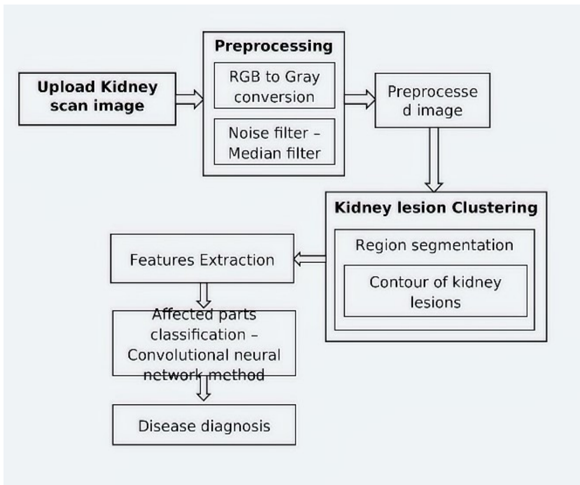

Fig 4: Proposed framework

The input picture size is sent to the network as (224,224,3). The VGG 16 consists of 16 layers, including fully connected+ReLU, conventional+ReLU, softmax, and maxpooling. Each layer completes its task for the uploaded image and produces an effective result. We may extract vectors like form, color, and structure by using this layer. Each hidden layer uses ReLU as its activation function. ReLU makes learning more rapid and reduces the possibility of vanishing gradient problems, making it more computationally effective.

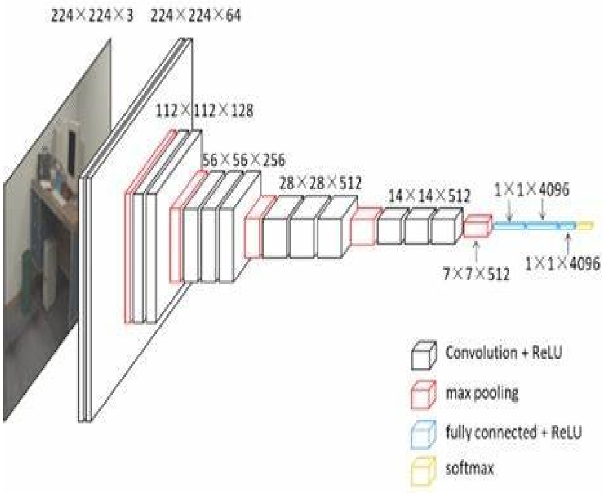

Fig 5: VGG16 architecture

IMAGE ACQUISITION: Worldwide, kidney disease is on the rise, yet most sufferers are unaware of it since it progressively harms their organs before symptoms show. Kidney illness must be detected early and prevented to improve sexuality. You may upload scanned photographs of any kind and size with this module.

PREPROCESSING: Pre-processing describes operations on images that are carried out at the most fundamental level of abstraction. The input and output are images of intensity. These symbolic pictures share the same characteristics as the real data that the sensor first recorded. Images of intensity are often represented as a matrix of brightness values for the image function. There are four main kinds of picture pre-processing approaches, depending on the size of the pixel neighbourhood used to determine the brightness of a new pixel. Pre-processing aims to improve image data, reduce unwanted distortions, and increase picture qualities that are essential for further processing. Here, the pre-processing includes the geometric modifications of the picture (rotation, scaling, translation, etc.). 2nd hand. The kidney picture of interest must be chosen by the user for additional processing. After that, each image is resized to 256*256. Next, apply a median filter on the cardioid His picture to eliminate noise. The method of median filtering, a nonlinear digital filter, is frequently used to eliminate noise from signals or pictures.

SEGMENTATION: Active contours are often employed in image processing to create closed contours for areas and define smooth forms in photos. Finding asymmetrical shapes in photographs is its major objective. For segmenting medical images, a variety of applications employ active contours. In a range of medical applications, active contour algorithms are mostly used to extract valuable areas from various medical pictures. For instance, active contour models are used to assess the segmentation of a slice of a brain CT scan.The technique of breaking up large datasets into more manageable groups of related data is known as data clustering. Finding the curb could be quite challenging since it appears to be so black in a specific image. The feature extraction approach used in this module takes data from already-processed photos and extracts details like colour, shape, and texture. Each grey level is proportionally present in the final image. Kidney stones can be seen in the images from an ultrasonography.

CLASSIFICATION: Neural networks have made tremendous advancements in the analysis of medical imaging data. Wavelets and the neural network idea are used to create a computer-aided design (CAD) system for identifying kidney stone features. The VGG-16 algorithm is used to categorize illnesses. VGG-16 is the name of the object detection and classification algorithm. We created a CAD system to detect kidney stones because wavelets and neural networks combine effectively. A feed-forward neural network called a BPNN combines entirely connected, max-pooling, and hidden layers in various ways. Maximal pooling layers and hidden layers alternate to mimic the detailed and well-organized cellular uniqueness of the mammalian brain via spatial proximity correlation by pushing stiff connection patterns between neurons in nearby levels to grow. A fully connected neural network, or CNN, is made up of one or more pairs of layers with maximal pooling and perceptron technology. As CNNs have repeatedly demonstrated, theirs is the most effective hierarchical structure for processing visual representations. A major challenge in such visual work is modeling variations in shape and appearance within object classes. Two-dimensional curves can be used to represent visual data with several spectral channels. Even though certain classes are more difficult for the human eye to distinguish than others, each class curve has a unique visual feature that distinguishes it from the others (e.g., gravel and self-blocking stone). We should consider using CNNs to classify character traits given that they outperform humans in a range of visual tasks. The implementation, training, size, and number of output classes of the convolutional and max pooling layers all affect the performance of a CNN.

DISEASE PREDICTION: The VGG neural network technique is used in this module to recognise various kidney disorders. Cysts, stones, tumours, and normal kidney function are the four main kidney illnesses. Round fluid sacs called kidney cysts can develop on or inside the kidney. Kidney function can be impacted by renal cysts. It could be linked to severe medical issues. Hard deposits of minerals and salts called kidney stones form in the kidneys.They are also referred to as nephrolithiasis, nephrolithiasis, and urinary calculi. There are benign (noncancerous) and malignant kidney tumours. (cancer). benign kidney tumours make for 25% of cases. Smaller masses are frequently benign. The CNN categorization allows for the identification of the renal disease and the provision of diagnostic data based on the presence of the renal disease.

VI. EXPERIMENTAL RESULTS

The kidney dataset obtained from the KAGGLE source is accepted as an input for this investigation. Sensitivity parameters are used to assess system performance after being implemented in a Python framework.

The proportion of perfect positive predictions to all positive predictions is used to calculate sensitivity (SN). The maximum sensitivity is 1.0, while the minimum sensitivity is 0.0.

$$SN = \frac{TruePositive\,(TP)}{TruePositive\,(TP) + TrueNegative\,(TN)}$$

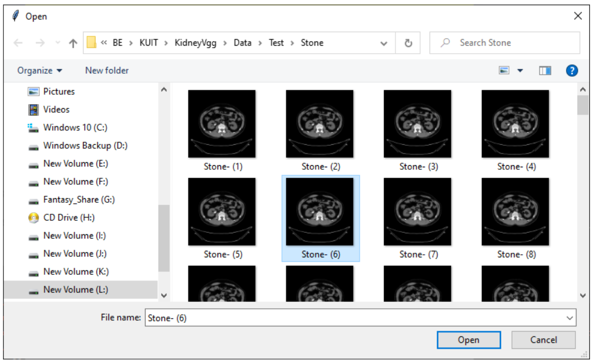

Fig 6: Dataset

Table 1: ACCURACY VALUES

ALGORITHM	SENSITIVITY
DECISION TREE	0.75
RANDOM FOREST	0.85
CNN CLASSIFICATION	0.94

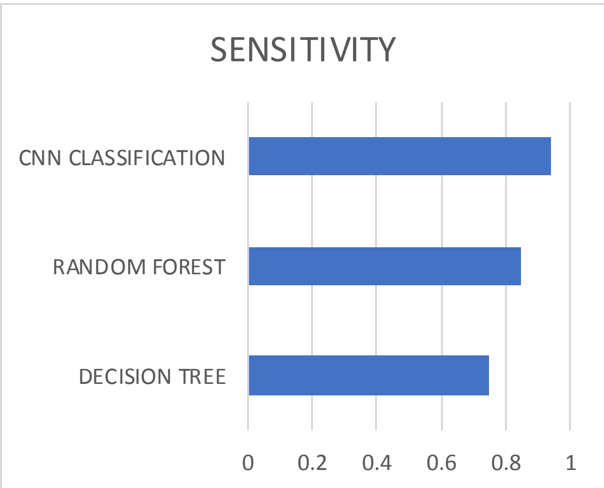

Fig 7: Performance evaluation

From the above figure, the proposed system provides improved efficiency than the existing algorithms. There are several algorithms that may be employed to identify kidney stones, but CNN classification stands out among them for its high accuracy and effective prediction. As a consequence, we classify CNN data to get superior results. By uploading datasets, we may apply the algorithms we employed in our study to diagnose renal illness; after analysing several of the algorithms, CNN produces the best results.

VII. RESULT AND DISCUSSION

The use of deep learning techniques in this stud improves the ability to identify kidney stones. The VGG 16 method is highly accurate in detecting disorders and prescribing the right medications.

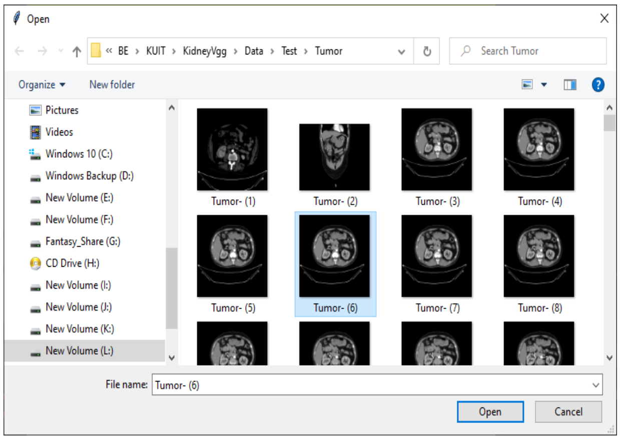

Fig 8: Image dataset

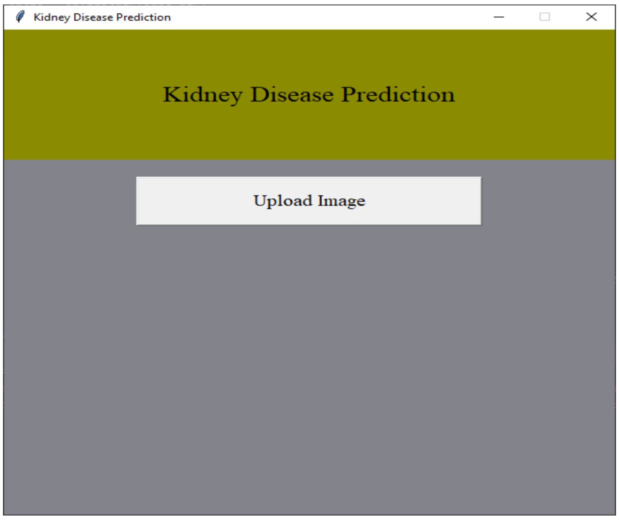

Fig 9: Uploading Image

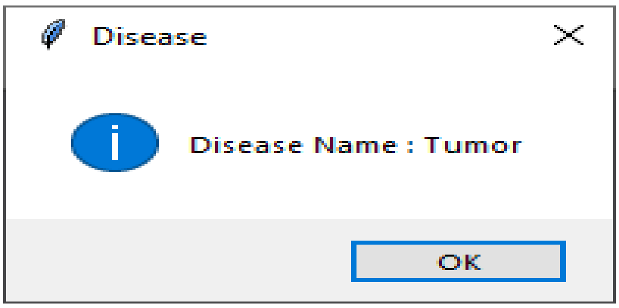

Fig 10: Disease Prediction

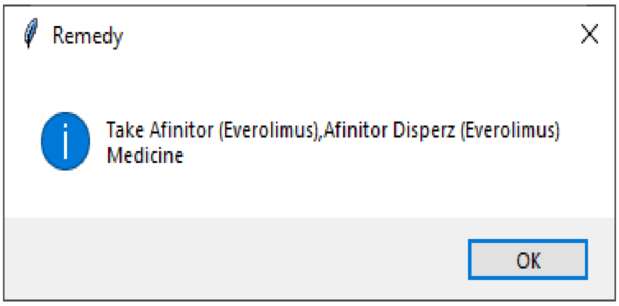

Fig 11: Disease Remedy

VIII. CONCLUSION

Because CT scan pictures are unique to each patient and do not match across individuals, diagnosing kidney stones is a challenging assignment for medical professionals. As a result, the doctor may use this method to automatically extract information from the patient's CT scan and forecast the presence of stones based on those traits. The created technology speeds up diagnostics while increasing their precision. The findings show that textural characteristics may be utilised to categorise various kidney disorders. The findings further show the viability of employing histology techniques to create CAD and computer-aided kidney stone categorization systems and to create suitable decision-making guidelines. Utilize guided active contouring and classification methods employing convolutional neural network algorithms to analyse more pictures and more precisely detect sick regions.

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