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Automated Kidney Stone Detection using Coronal CT images based on Deep VGG-19 Model

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***Abstract*—Kidney stone detectors appear to be a significant difficulty for identifying a kidney stone illness. Identifying a kidney stone may need a method that guarantees accuracy and also is in broad usage. An automated diagnosis of kidney stone (having stone/not) utilizing coronal computed tomography (CT) pictures is suggested utilizing the deep learning (DL) method that has lately achieved considerable development in the area of artificial intelligence. The main aspect of this study is the identification of the afflicted part of the kidney stone picture. Kidney stone diagnosis is one of the sensitive issues presently. Many issues are associated with this subject, such as the poor resolution of a picture, a resemblance of kidney stone & predictions of stone in the new picture of kidney. Ultrasound pictures have poor contrast or are hard to identify & extract the area of interest. Therefore, a picture needs to go thru the preprocessing that usually includes image enhancement. In this work, we have developed the VGG-19 CNN model, which is the DL method. The VGG19 has several layers. However, as the network becomes deeper, overfitting will be an issue that needs to be addressed. This issue is addressed through data augmentation. A total of 1799 pictures were utilized by obtaining separate cross-sectional CT scans for every individual. The developed automated prototype demonstrated precision utilizing CT pictures in identifying a kidney stone. We have noticed that our model cancorrectly identify kidney stones of even tiny size. Our created DL framework produced good outcomes with this dataset and is suitable for clinical use. This research demonstrates that lately used DL techniques may be utilized to solve additional difficult issues in urology.**

***Keywords*—Kidney stone, Computed tomography, Deep learning, CNN, XResnet-50, VGG19.**

I. INTRODUCTION

With the advancement of technology, several computer-aided schemes for identifying the presence of illness have been developed, focusing on system accuracy. The chapter explains how to use soft computing abilities to perform several processes in computer-assisted medical diagnosis. Artificially intelligent decision support systems for illness identification and treatment are also covered, as well as the reason for undertaking this study, different stages of study, & contributions. The goal of CAD technologies is to create an image segmentation tool that can identify cysts autonomously & integrate them into a knowledge-based artificial intelligence decision support system.Furthermore, telemedicine enables the use of current telecommunications & information technology for the delivery of clinical treatment to persons in remote regions and the communication of data to do so. A radiologist's expertise is used to provide a diagnosis. Similar pictures have been used as an indicating help in illness prediction in studies such as. CAD has refined a digital approach that randomly chooses the same pictures from a database for identifying similarities & associations among sick tissues & stones and goal features of morbid tissues & stones.[1].

Kidney stones are still a fairly frequent condition, impacting around one out of every 10 persons at a certain time in their lives. The prevalence of kidney stones seems to have grown over the last several decades. While this could be discussed in parts by enhanced identification, at least some of this is attributable to diet modifications & growing levels of obesity. Imaging is crucial in caring for patients with renal stone illness, involving original diagnosis, care plans, & follow-up following medicinal therapy or urologic procedures. [2].Kidney stone illness (nephrolithiasis) is a frequent form of urology illness with a large incidence rate of 10% after one year, 50% after 5-10 years, & 75% after 20 years. Over the previous 20 years (1991-2011), the prevalence rate of kidney stones illness in China has nearly doubled, from 5.95 percent to 10.63 percent, as recorded on the mainland. Because of the lack of particular symptoms in the initial stages of this illness, it is hard to diagnose the issue.And it's after this first evidence of organ failure that it's discovered. Furthermore, kidney disease is a chronic condition that damages the kidneys, resulting in a persistent & unresolved issue. As a result, detecting kidney stone illness early irreparable damage occurs is critical. Kidney disease could be efficiently addressed if the stone fault is identified earlier on. As a result, stone detection is critical not only for the treatment of renal illness but also for the management of recurring stone development.

In previous years, 3D medical image processing has played an increasingly important role in computer-assisted diagnosis, assisting radiologists in assessing medical imaging and identifying aberrant findings in medical images. Kidney stone disease is diagnosed using conventional tests (blood tests, urine tests, & biopsies) & imaging tests (ultrasound, CT, & MRI). Imaging tests utilizing computer tomography (CT) have become the most frequent amongst diagnostic tests, depending on time spent, expense, and information received from diagnostic testing.However, due to the complex structures of interest in abdominal

CT, stone diagnosis on CT is still a problem in segmentation. Because of the heterogeneous nature of the tissue, the lack of obvious borders, the similarity of nearby organs, noises, and the partial-volume impact, precise organ segmentation is a challenging task. As a result, the preprocessing approach is critical for enhancing 3D picture segmentation results. [3].

Deep learning (DL) methods have been effectively widely used in clinical pictures & physiological data in various disciplines. Deep architectures have been effectively applied in various applications, including medical picture segmentation, categorization, & lesion identification. Numerous types of health pictures, like magnetic resonance imaging (MRI), computed tomography (CT), & X-ray, were used to create robust and accurate DL models to help clinicians diagnose illnesses like Covid-19, cardiac arrhythmia, prostate cancer, brain tumour, skin cancer, & breast cancer. In the area of urology, DL techniques are used to identify ureteral stones & kidney stones automatically. [4] .

The rest of the article is structured in the following way: Section II contains relevant published work. Section III present the problem statement, proposed methodology and introduces VGG-19 Deep CNN Model. The IV section presents the experimental results.The last sections define the conclusion and future scope of the proposed method.

II. REVIEW OF LITERATURE

There have been muchresearches carried in the fields of this image processing for kidney stone detection.Researchersused many kinds of algorithms to find the stone in a kidney.

This work [4]proposes utilizing the deep learning (DL) approach, which has lately made considerable development in the area of artificial intelligence, automatic identification of kidney stone (having stone/not having stone) utilizing coronal computed tomography (CT) pictures. By obtaining separate cross-sectional CT scans for every participant, a total of 1799 pictures were used. The accuracy of our created automatic framework in identifying kidney stones utilizing CT images was 96.82 percent. We've discovered that our framework can identify kidney stones of any size, even for the tiniest ones.With a bigger dataset of 433 individuals, our created DL prototype outperformed the competition and is prepared for clinical use. This work demonstrates that increasingly popular DL techniques may be used to solve additional difficult urological issues.

This study [5] suggests utilizing transfer learning to automatically classify B-mode renal ultrasound pictures to use an ensemble of DNNs. Speckle noise affects ultrasound pictures, &better-quality evaluation in ultrasound picture data is dependent on a perception-based picture quality assessor score. The pre-trained DNN method is described 3 different datasets with feature extraction, following by the SVM for classifications. The majority voting approach is used to integrate multiple pre-trained DNNs such as ResNet-101, ShuffleNet, and MobileNet-v2 to make final predictions. In testing using good pictures, the provided approach had the highest classification accuracy of 96.54 percent, while in testing using noisy images, it had a high classification accuracy of 95.58 percent. Precision, sensitivity, & selectivity are used to assess the effectiveness of the proposed technique.

The goal of this work [6]has been to create a reader-independent preprocessing method for detecting & segmenting kidney stones in CT images. Unwanted areas are removed using 3 thresholding techniques that rely on intensity, size, & location, like soft-organ removal, bony skeleton removal, & bed-mat removal. The analysis of the data & validity used digitized transversal abdominal CT scan pictures for 30 individuals with kidney stone cases.Expert radiologists independently assessed the estimate of coordinates locations in stone areas as validated data for analysis. The suggested preprocessing procedure has 95.24 percent sensitivity as an assessment factor, according to experimental evidence. As a result, using effective detection may decrease noise & undesirable areas in every operation.

This work [7]suggests a convolutional neural network-based automatic structure for detecting different kidney problems on abdominal ultrasound images. The Mf-Net additionally includes a multi-feature fusing layer for extracting unique characteristics from various picture perspectives. According to the outcomes, the suggested ensembles detection method outperforms a competition with an average TPF of 98.0 percent or an average categorization precision of 94.67 percent. The excellent categorization & detection accuracy achieved show that the suggested approach is efficient in detecting kidney problems.

The proposed [8] work detects kidney stones by using the Level set segmentation method. Initially, input images are preprocessed, and the region of interest is segmented. The level set segmentation is a good method to resolvetheissue of segmentation successfully. The preprocessing of the CT images is carried out for cropping the input image. After preprocessing step, the input image is segmented using the level set segmentation technique. Finally, the segmented images are analyzed to identify the size & location of the stone.

On an Internet of Medical Things (IoMT) framework, a Heterogeneous, Modified Artificial Neural Network (HMANN) has been suggested for early detection, segmentation, and diagnosis of chronic renal failure in this study [9].The suggested HMANN is also categorized as a Support Vector Machine (SVM) and a Multilayer Perceptron (MLP) using a BP method. The suggested technique is dependent on a preprocessing phase in which an ultrasound picture is divided to identify the region of interest as in the kidney. The suggested HMANN technique for kidney segments provides excellent accuracy while decreasing the time it takes to define the shape.

The Back-Propagation Networks were used in this study [10]to identify kidney stones. Feature extraction & picture categorization are the two steps of decision making. A principal component analysis is used for feature extraction, while Back

Propagation Networks is used for picture categorization (BPN). The Fuzzy C-Mean (FCM) clustering technique is used to propose a segmentation approach in this article. The BPN classifier's efficiency was evaluated in terms of training efficiency & categorization accuracy if contrasted to those other neural network-based techniques, the BP Network that provides exact categorization.

A computer-aided diagnostic (CAD) method for identifying multi-class kidney problems from ultrasound pictures is proposed in this work [11].The described CAD systems extract features using a pre-trained ResNet-101 framework & classify them using a support vector machine (SVM) classifiers. Ultrasound pictures are frequently impacted by speckle noise, which affects picture quality & CAD system efficiency. As a result, a CAD-based system with a DE speckling module that uses a deep residual learning network (RLN) to minimize speckle noise is presented. Deep RLN preprocessing of ultrasound pictures improves the CAD system's categorization effectiveness dramatically.

III. PROPOSED WORK

A. Problems Statement

When one of your kidneys starts to fail, it may be terrifying. As a result, it is critical to identify kidney stones as soon as possible. The effectiveness of surgeries depends on the accurate diagnosis of kidney stones. The poor contrast & speckle noise in renal ultrasound pictures create it hard to detect kidney problems. Therefore, physicians could find it hard to recognize tiny kidney stones & their kind properly detecting small stones & their type. Additionally, it has to deal with the issue of overfitting.

B. Proposed Methodology

We have proposed a deep learning-based VGG-19 CNN pre-trained model to detect kidney stones using CT images to overcome the above problem.'VGG16' has been selected as the pre-trained network for our suggested learning model since it is well & widely used. This is the initial time we're collecting data from[12], and after this, we have to perform preprocessing. In preprocessing phase consists of image resizing and image scaling. After taking preprocessed images, data augmentation has been performed to generate new data and solve the overfitting problem. Data augmentation contains a variety of picture editing techniques, including shifting, flips, zooms, & resizing. Lastly, this enhanced dataset was used to train a VGG-19 framework. The VGG19 model's properties were fine-tuned using Adam optimization method or a loss function. This study's early experimental results indicate that the VGG19 has a higher categorization accuracy than the alternatives. Thus traditional & customized VGG19 are taken into account in this study to improve kidney stone identification precision.

1) Data preprocessing

Preprocessing is used to enhance a low-contrast ultrasound picture with speckle noise that has been collected. Picture resizing & scaling are used as part of the preprocessing procedure. Pictures at smallest level of abstraction are used in both input & outcome pictures during preprocessing. As the initial pictures recorded by certain sensors could have lower intensity, the picture typically expressed by a brightness function matrix must be created. It is essential to improve the picture data for stone identification & subsequent processing utilizing picture preprocessing. The picture quality of the United States may not even be suitable for analysis if it has not been preprocessed. The precise location of a kidney stone must be determined before procedure can begin. To combat poor contrast & speckled noise removal, preprocessing is helpful.[13].

2) Data Augmentation

One of the most well-known data enhancement methods includes generating new pictures from training datasetsthat are similar to the initial ones. Transforms included many picture modification techniques, including shifts, flips, zooms, & many more. It's a method for increasing data volume & complexity. Instead of transforming alreadyavailable information, we'll gather new information. As a result, it's a step in the deep learning processes because we need a large amount of data for DL & sometimes it's not feasible to collect dozens or even millions of pictures. It enables us to get the most out of our datasets.

C. VGG19 Network Model

As of 2014, Simonyan& Zisserman of Oxford University's Computer Laboratory developed a pre-trained CNN framework called VGG networks[14].ImageNet ILSVRC dataset of 1.3 million pictures has been used to train VGG (Visual Geometry Group), with 100,000 pictures in use for training & 50,000 pictures in use for validation. Compared to other current state-of-the-art prototypes, VGG-19, a version of VGG structures with 19 highly linked layers, regularly outperformed it. To improve feature extraction & usage of Maxpooling (instead of average pooling) in down-sampling before categorization utilizing SoftMax activation function, its framework incorporates strongly connect convolutional &fullyconnected layers. By layering the low- & high picture characteristics, VGG-19 Net [15]attained identification precision while also achieving picture categorization in the process. Data gathering, data preprocessing, prototype training, prototype testing, & model validation comprise the bulk of the identification procedure in this article. There are six major VGG CNN architectures, which are primarily made up of several linked convolutional layers & fully connected layer configurations. 3*3 convolution kernel with input size of 224*224*3 is used in this example. The most common no. of layers is between 16 to 19. Figure 1 depicts a VGG-19 model's design.

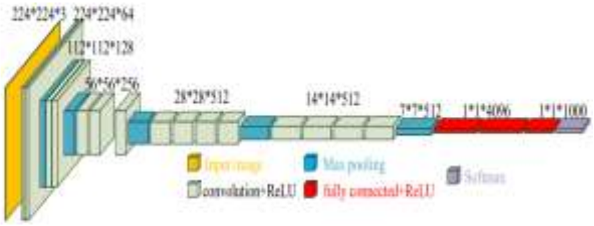

Figure 1. VGG-19 network model

VGG-19 The CNN preprocessing structure is employed. It has a deeper network than conventional CNN. Instead of using only one convolution, it alternates between several convo layers & non-linear activation layers. Maxpooling for downsampling&alteration of linear unit (ReLU) as an activation function may be achieved by using a layer structure that extracts picture characteristics effectively & uses Maxpooling. The major purpose of downsampling layer is to enhance the network's anti-distortion capabilities to picture while preserving a sample's primary characteristics & decreases the amount of factors. [16][17][18].

1) Loss function

The loss function measures how much the method's existing outcome lags behind the anticipated one. Your method's ability to prototype the data is evaluated using this technique. It may be divided into two categories. Both may be used for classifications (discrete values, 0,1,2…) &regression (continuous values).

- **BinaryCrossEntropy**

Classification tasks often utilize the loss function binary cross-entropy. Usually, there are just 2 options for responding to a question (yes or no, A or B, 0 or 1, left or right). In multi-label categorization or binary picture segmentation, many separate queries may be addressed simultaneously. According to math, this loss is equal to a mean of all category cross-entropy losses on all two-category problems.

When using a binary cross-entropy loss function, the following average is used to compute the loss:

$$\text{Loss} = -\frac{1}{\substack{\text{output}\\\text{size}}} \sum_{i=1}^{\substack{\text{output}\\\text{size}}} y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot \log(1 - \hat{y}_i)$$

if $\hat{y}_i$is the prototype output's i-thscalar value,$y_i$is the equivalent target value, & output size is a number of its scalar values in a prototype outcome.

This is the same as the average result of applying a categorical cross-entropy loss function to a large no. of independent classifications issues, for each issue having just two possible classes & target probability $y_i$and (1-y_i).

2) Adam Optimizer

A picture file optimization is a service, product, or library that makes large images smaller. Picture optimizers compress & resize images to decrease file size while maintaining picture quality. This study made use of the Adam optimizer. Instant Assessment (Adam) is a method for calculating the adaptability of learning rates. And as well the RMSprop &Adadelta, Adam has an exponentially decaying average of prior square gradients v_tAnd an exponentially decaying average of prior gradients m_t. Although momentum may be compared to a slope-running ball, Adam prefers flat minima on a surface of error, acting as a high friction ball. For each successive square gradient, we compute decaying averages of two variables: m_t&v_t.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$
$$v_t = \beta_1 v_{t-1} + (1 - \beta_1) g_t^2$$

Since the first & second moments of gradients have been calculated, they may be referred to as $m_t$and v_t Respectively. Since the initialization of m_t& v_t avector of zeros, Adam researchers, have found that they will be biassed towards zero, particularly in the earlier stages and if decay rates are low (so that β_1& $\beta_2$are nearly 1).

3.4 Proposed Algorithm

step1	Start
step2	Collect the input images of Kidney_stone_detectionfrom GitHub.
step3	Preprocess the data to remove the noisy data with the help of image resizing and image scaling.
step4	Perform data augmentation on processes data with the help of Zoom range, Rotate techniques.
step5	Divide data into train and test set
step6	Trained the augmented data with the VGG19 CNN model.
step7	Test the model.
step8	Obtain Predicted Results.
step9	End

3.5 Proposed Flowchart

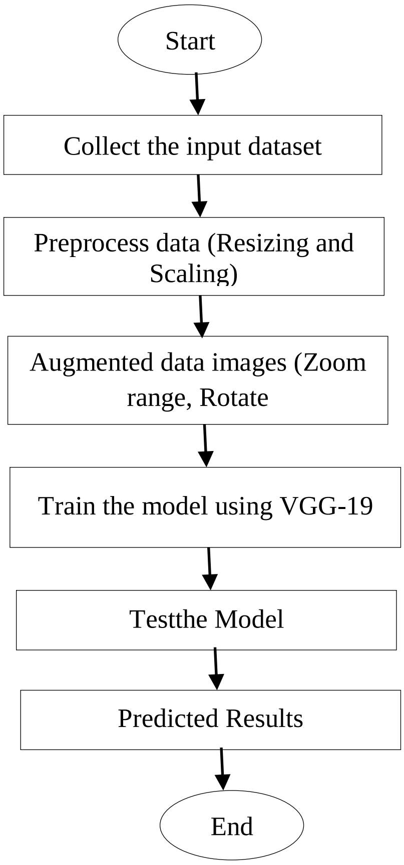

Figure 3: Proposed Flowchart

IV. RESULTS AND DISCUSSION

This work has been carried out with the help of the Python programming language as well as the target platform was Jupyter notebook. The total no. of images in the training dataset is1799.

A. Samples of images

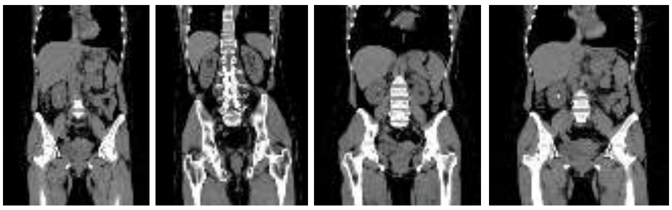

Figure 3: Kidney Stone

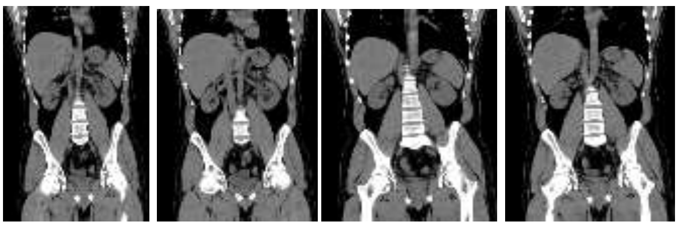

Figure 4: Normal

Table 1. Class label

Category	**Label**
Kidney Stone	0
Normal	1

B. Splitting dataset

80 percent of 1453 CT scans were utilized in the model's training stage, with the other 20 percent for validation. Three hundred and forty-six pictures not included in the deep model's training were also used to generate test efficiency results after the framework was finished being trained. To train a framework, one must use training data; to validate a prototype, one must utilize validating data alone.

Train Dataset split into training and validation

- Training dataset (80%)
- Validation Dataset (20%)

C. Experiments

Weperformed atotalnumberofthreeexperimentsonournetworkwith differenceinthenumberofepochs andwithanadditional layer.

Experiment-1Forfirstexperiment,weused20epochs,themodellearnedfromthetrainingdata.

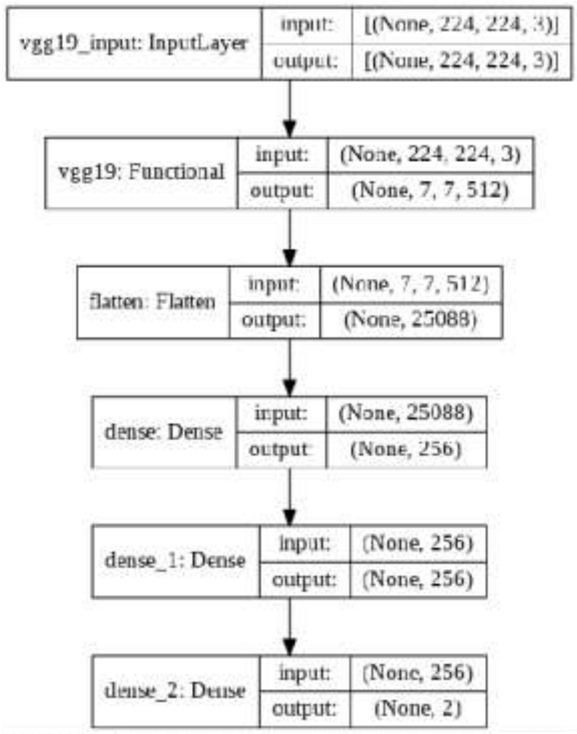

Fig5:Proposedstepsofmodelwith20epochs

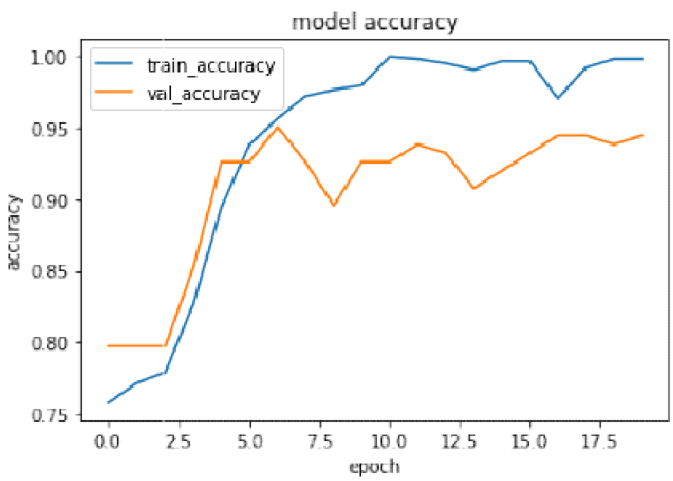

Figure6:ProposedDeepVGG-19ModelAccuracyGraphfor20epochs

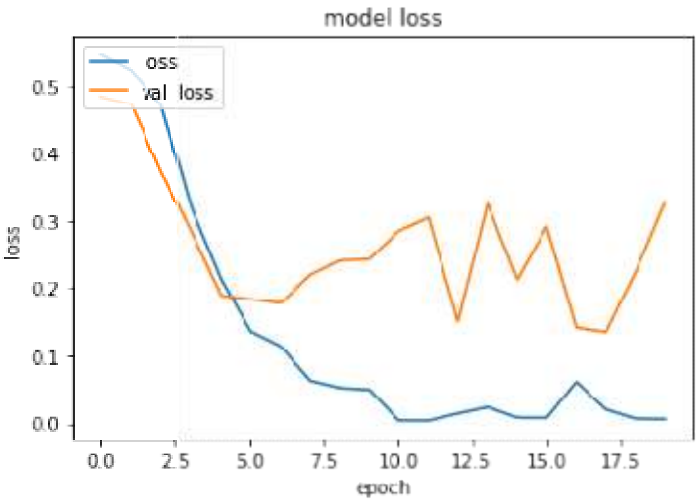

Figure7:ProposedDeepVGG-19ModelLossGraphfor20epochs

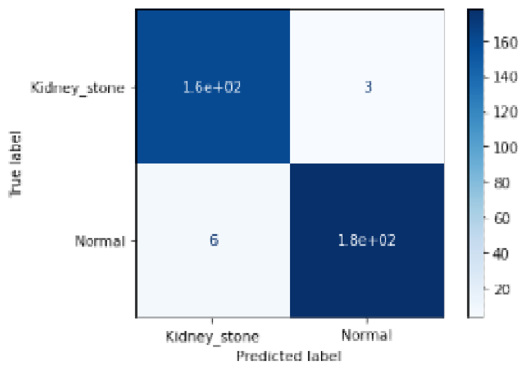

Figure8:Confusionmatrixbasedontestdatafor20epochs

Experiment-2 To improve efficiency we used 30 epochs with an additional layer, the modellearned from the training data. In Figure 8, the test data-generated confusion matrix is shown. Theconfusionmatrixshows thatthemodelaccurately identified158pictures ofkidneystones(true positive, TP) with 7 photos of kidney stones in normal class (no abnormality) (falsenegative,FN).

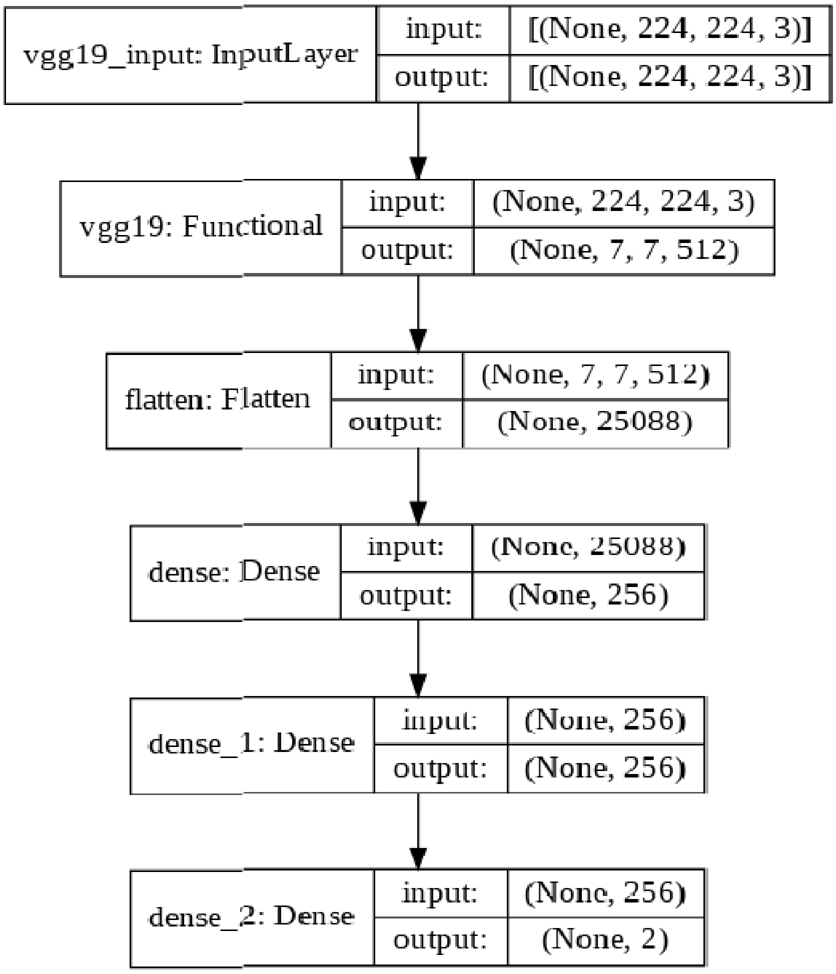

Fig9:Proposedstepsofmodelwith30epochs

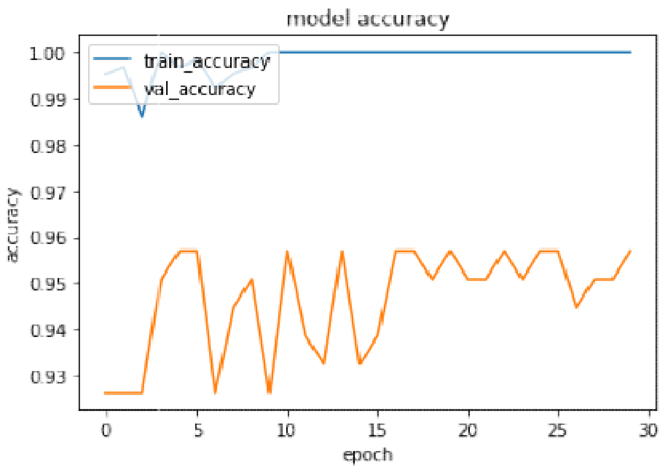

Figure10:ProposedDeepVGG-19ModelAccuracyGraphfor30

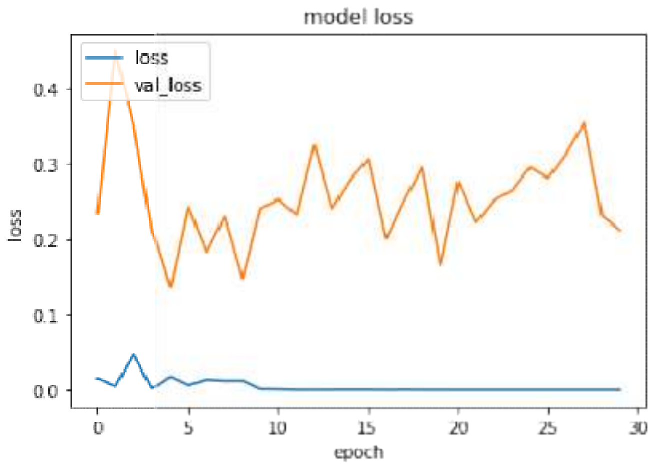

Figure11:ProposedDeepVGG-19ModelLossGraphfor30epochs

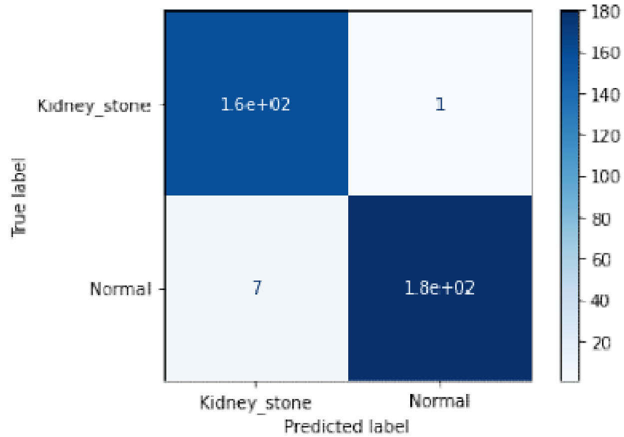

Figure12:Confusionmatrixbasedontestdatafor30epochs

Experiment-3To further improvetheaccuracy we used 30 epochs andthe model was trained.Inthisexperimentthemodelaccuratelyidentified177picturesasbelongingtothenormalclass(alsoknownastruenegatives,or TNs).4picturesofnormalpeople(FalsePositives,FP) were mistakenly identified as kidney stones. Metrics e.g. recall and precision have beenappliedtoassessthemodel'scorrectness.Anessentialcriterion forassessingthemodel'ssuccess is toconsider various indicatorsall at once.Soto conclude our third experimentperformedoptimallyanditsvalidationandaccuracyisasfollows.

D. ValidationandAccuracy

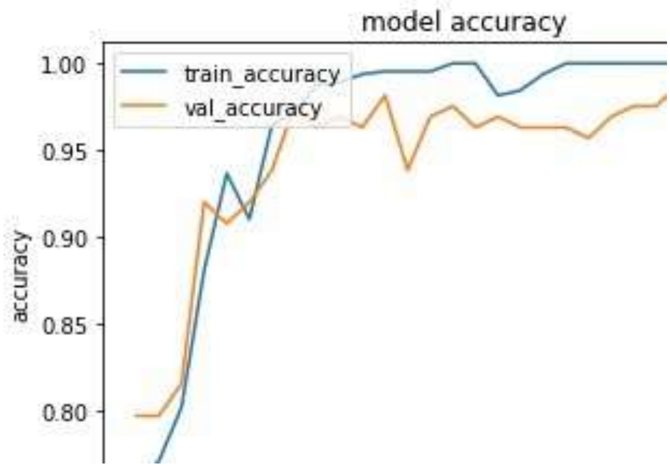

Figure13:ProposedDeepVGG-19ModelAccuracyGraph

Figure 13abovedemonstrates acomparisonbetween training & validation preciseness.For30 iterations, the framework learned from training data. During DL model training, this graphshows the precision rate & loss values for every epoch. As you can see, the x-axis shows theamount of prototype training epochs thatcorrespond to the total amount of times thedatasethas been cycled through, and the y-axis shows precision. If you look carefully at the precisiongraph, you'll see that validation accuracy is greater than training precision for certain initialepochs.

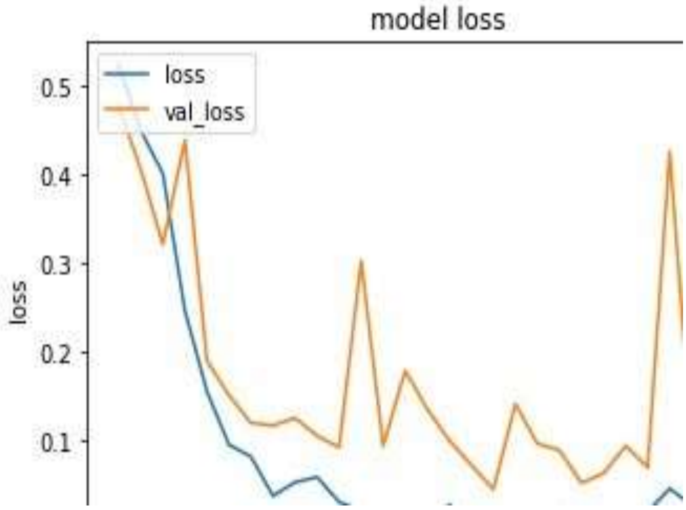

Figure14:ProposedDeepVGG-19ModelLossGraph

In above figure 14 shows the training loss and validation loss graph. For 30 iterations, the framework learned fromtraining data. With atraining loss that'sdecreasing &continuing todoso,thisframeworkisdiscovered.ValidationisdonebyrunningtheCNNthruthespecified setup. Individuals' CT scans are used to determine which & how many items areidentifiedas stonesaspartofaprocedure.

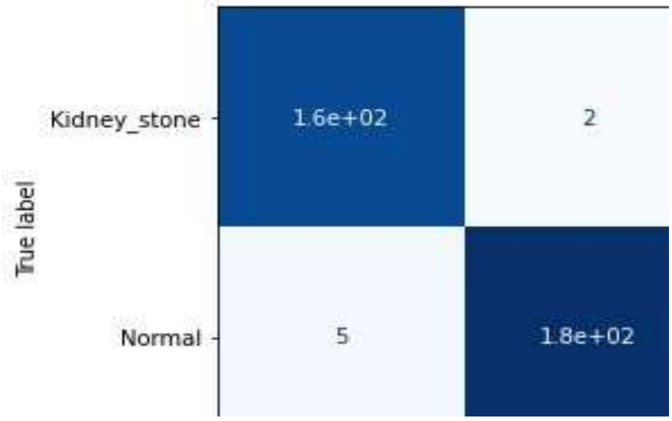

Figure15:Confusionmatrixbasedontestdata

Fig.15 shows the confusion matrix derived fromthe testing data. The confusion matrixshows5kidneystonepicturesinthestandardclass,whereastheframeworkaccuratelypredicted16e+02kidneystonepictures(truepositive,TP)(falsenegative,FN).18e+02TN wasproperlyidentifiedasnormalbytheframework.However,itmisclassifiedtworegular pictures as kidney stone pictures, FP. The confusion matrices were obtained as theresultsofa classification method.

COMPARISONAMONGVARIANTSUSED

Table2:Base&SuggestedPrototypeComparison

Variant		Precision	Recall	f1-score	Support
20Epoch	KidneyStone	0.96	0.98	0.97	163
	Normal	0.98	0.97	0.98	184
30 Epoch withadditionallayer	KidneyStone	0.96	0.99	0.98	160
	Normal	0.99	0.96	0.98	187
30Epoch	KidneyStone	0.99	0.94	0.97	174
	Normal	0.97	1.00	0.98	353

COMPARISONWITHEXISTINGMODEL

Table3:Base&SuggestedPrototypeComparison

Model	Loss	Accuracy
XResnet-50	0.08118	0.91882
VGG-19	0.1672	0.9816

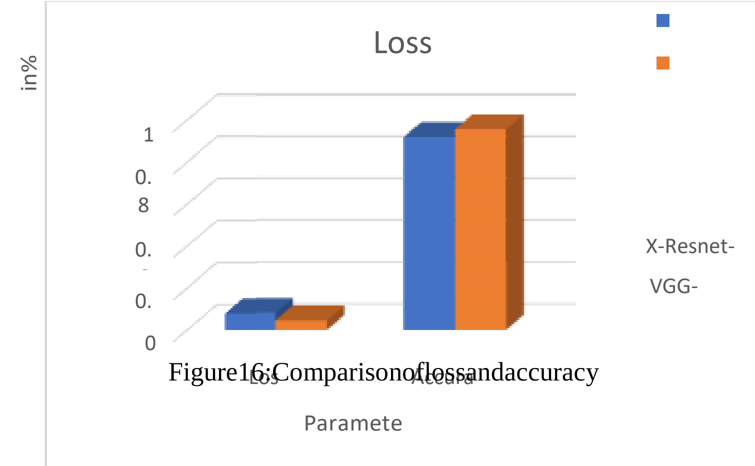

Figure16:Comparisonoflossandaccuracy

The above figure 16 and table 3 show the comparison graph of theXResnet-50 and VGG-19 model of training accuracy for input datasets. Graph and table clearly show the proposedmodel givenhigheraccuracy comparisonto exiting XResnet-50classifier fromthedatasets.Fig4.6illustratesthebargraphtocompareexistingXResNet-50andtheproposeddeepVGG-19 model in terms of accuracy & loss value. The value is represented in %. ExistingXResnet-50given91%accuracyandVGG-19given95%accuracyintraining.

IV. CONCLUSION

The DL framework developed in this research uses CT pictures to identify kidney stone patients. Additionally, our deep framework was able to identify areas of interest throughout the decision-making procedure based on a categorization of coronal CT scans. Two specialists looked through the findings & came to their conclusions (one radiologist and one urologist). Most of pictures' clinical areas were agreed upon by our medical specialists and those indicated by framework. As a result, the DL prototype we've created is precise or may help radiologists find kidney stone patients. The project's outcomes were positive, as urethral stone detection & categorization had a high degree of accuracy & precision loss. Our computerized framework demonstrated that CT scans were 100 percent accurate in identifying kidney stones.

V. FUTURE ENHANCEMENT

Using CT images to classify stones, future research should look for better CNN compositions from the one employed in this study. To do this, you may alter a design of the system, which may involve adding or removing layers of convolutions or pools and the activation & error functions that are being utilized. Because the search was thorough, future work must not be limited to altering hyperparameters within the same framework. Future research is required to determine whether digital endoscopy could utilize DL to identify stone composition. Using this technique, surgical effectiveness could be improved by autonomously providing lasers parameters depending on stone composition identification during endoscope & laser procedures.

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