Kidney Stone Detection Using Deep Learning

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Abstract- *Kidney stones are a common complaint worldwide, causing many people to admit to emergency rooms with severe pain. Various imaging techniques are used for the diagnosis of kidney stone disease. Specialists are needed for the interpretation and full diagnosis of these images. Computer-aided diagnosis systems are the practical approaches that can be used as auxiliary tools to assist the clinicians in their diagnosis. In this study, an automated detection of kidney stone (having stone/not) using coronal computed tomography (CT) images is proposed with deep learning (DL) technique. To remain healthy, cells grow and divide in orderly fashion. When cell growth becomes uncontrollable the extra mass of cell transforms into stone. CT scans and MRI are used for identification of stone. A novel kidney segmentation method for Computed Tomography patient data with kidney cancer is proposed. The segmentation process is based on Fuzzy C-Means Clustering Algorithm. It becomes very important to detect the stone and classify it at the early stage so that appropriate treatment can be planned. This CT scans are visually examined by the physician for detection and diagnosis of kidney stone. However this method lacks accuracy and detection of size of the stone. So to overcome this, a computer aided segmentation technique has been proposed, which extracts the stone part from the kidney, further on which feature extraction method is performed for extracting certain features using ResNet50 and for classification also performed to find the type of stone (Malignant or Benign).*

Keywords- Deep learning, Fuzzy C-Means Clustering Algorithm, ResNet50

I. INTRODUCTION

Kidney stone disease is one of the most common health problems, although the frequency varies between different countries. In prevalence studies, this rate is reported to be between 1 and 20%. Kidney stones can lead to kidney failure, loss of workforce by causing severe pain and decrease in the quality of life by obstructing the urinary system. For example, more than 2 million people in the United States of America (USA) apply to the emergency department every year for renal colic or stone-related back pain. Approximately half of these patients undergo non-contrast computed tomography (NCCT).

The studies on the diagnosis of this disease can improve the quality of life of patients and possible kidney failure. Although the selection of right imaging technique for the detection of kidney stones varies according to the clinical situation and patientrelated parameters, however, it is still the first step in the diagnosis of the disease. Ultrasonography (USG), kidney ureter bladder (KUB), NCCT are used to detect urinary system disease. NCCT has become the standard imaging modality for the diagnosis of acute flank pain.

In a meta-analysis, low-dose NCCT was found to detect with a sensitivity and specificity of 93.1% and 96.6%, respectively. Nowadays, deep learning (DL) techniques have been successfully applied to various fields using medical images and physiological signals. The deep models have been used successfully employed in many areas such as segmentation of medical images, classification, and lesion detection. Various types of medical images like magnetic resonance imaging (MRI), computed tomography (CT) and X-ray have been used to develop accurate and robust DL models to aid the clinicians in their diagnosis of diseases such as Covid-19, cardiac arrhythmia, prostate cancer, brain stone, skin, and breast cancer. DL techniques are also employed in the urology field for automatic detection of ureteral stones and kidney stones.

Proposed a CNN-based model to classify urinary stones from microcomputed tomography (micro-CT). They used a total of 2430 micro-CT slices and reported a test accuracy of 0.9959. developed a CNN model for classifying pelvic calcifications. They concluded that the CNN model results are better than the mean assessment by seven radiologists. It used a CNN model for identifying ureteral stones in thin slice CT volumes. In this study, a model was designed to prevent the missed stone diagnosis using CT images and minimize the physician-induced errors by using DL techniques. Most of the stone patients will be admitted to the emergency room and it may be difficult to get a specialist radiologist always. Sometimes the reporting period of computed tomography can be delayed due to the scarcity of radiologists. Misinterpretation may be encountered in cases where imaging is performed faster than usual.

In addition, since computed tomography reporting is a time-consuming process, the evaluation of kidney with computer-aided methods for early and accurate diagnosis will be a significant contribution to the health field. Urology is one of the branches of medicine which is using advanced technology for accurate diagnosis. The robots and endourological interventions have been employed in surgery in the field of urology. Nowadays, DL have been exceedingly used in healthcare application due to sudden explosion of data. In this study, we have made an effort to implement DL for the automated classification of kidney stone cases using CT images. The model can detect kidney stones. Also the proposed model can focus on kidney stone area on CT images.

II. LITERATURE SURVEY

In image processing, segmentation algorithms constitute one of the main focuses of research. In this paper, new image segmentation algorithms based on a hard version of the information bottleneck method are presented. The objective of this method is to extract a compact representation of a variable, considered the input, with minimal loss of mutual information with respect to another variable, considered the output. First, we introduce a split-and-merge algorithm based on the definition of an information channel between a set of regions (input) of the image and the intensity histogram bins (output). From this channel, the maximization of the mutual information gain is used to optimize the image partitioning. Then, the merging process of the regions obtained in the previous phase is carried out by minimizing the loss of mutual information. From the inversion of the above channel, we also present a new histogram clustering algorithm based on the minimization of the mutual information loss, where now the input variable represents the histogram bins and the output is given by the set of regions obtained from the above split-and-merge algorithm. Finally, we introduce two new clustering algorithms which show how the information bottleneck method can be applied to the registration channel obtained when two multimodal images are correctly aligned.

The visualization of medical volumetric data is an important area of scientific visualization. 3-D segmentation plays a critical role by facilitating automatic or semi-automatic extraction of the anatomical organ or region-of-interest. Segmentation s an important aspect of medical image processing, whose purpose is to extract the region of interest from the original images to provide a reliable basis for clinical diagnosis, pathological analysis and treatment. In this paper we introduce an adaptive region growing algorithm for image segmentation by estimating the parameters through investigation of the statistical characteristics in local regions. And through visualization technology, its segmentation results is showed. The experimental results demonstrate the simplicity and effectivity of the approach, and the results is in accordance with our understanding on the semantic concepts and the perceptual mechanism of human eyes.

This paper reports the results of a numerical comparison of two versions of the fuzzy c-means (FCM) clustering algorithms. In particular, we propose and exemplify an approximate fuzzy c-means (AFCM) implementation based upon replacing the necessary ``exact" variates in the FCM equation with integer-valued or real-valued estimates. This approximation enables AFCM to exploit a lookup table approach for computing Euclidean distances and for exponentiation. The net effect of the proposed implementation is that CPU time during each iteration is reduced to approximately one sixth of the time required for a literal implementation of the algorithm, while apparently preserving the overall quality of terminal clusters produced. The two implementations are tested numerically on a nine-band digital image, and a pseudocode subroutine is given for the convenience of applications-oriented readers. Our results suggest that AFCM may be used to accelerate FCM processing whenever the feature space is comprised of tuples having a finite number of integer-valued coordinates.

This paper deals with the implementation of Simple Algorithm for detection of range and shape of stone in brain MR images. Stone is an uncontrolled growth of tissues in any part of the body. Stones are of different types and they have different Characteristics and different treatment. As it is known, brain stone is inherently serious and life-threatening because of its character in the limited space of the intracranial cavity (space formed inside the skull). Most Research in developed countries show that the number of people who have brain stones were died due to the fact of inaccurate detection. Generally, CT scan or MRI that is directed into intracranial cavity produces a complete image of brain. This image is visually examined by the physician for detection & diagnosis of brain stone. However this method of detection resists the accurate determination of stage & size of stone. To avoid that, this project uses computer aided method for segmentation (detection) of brain stone based on the combination of two algorithms. This method allows the segmentation of stone tissue with accuracy and reproducibility comparable to manual segmentation. In addition, it also reduces the time for analysis. At the end of the process the stone is extracted from the MR image and its exact position and the shape also determined. The stage of the stone is displayed based on the amount of area calculated from the cluster.

Clustering approach is widely used in biomedical applications particularly for brain stone detection in abnormal magnetic resonance (MR) images. Fuzzy clustering using fuzzy C-means (FCM) algorithm proved to be superior over the other clustering approaches in terms of segmentation efficiency. But the major drawback of the FCM algorithm is the huge computational time required for convergence. The effectiveness of the FCM algorithm in terms of computational rate is improved by modifying the cluster center and membership value updation criterion. In this paper, the application of modified FCM algorithm for MR brain stone detection is explored. Abnormal brain images from four stone classes namely metastase, meningioma, glioma and astrocytoma are used in this work. A comprehensive feature vector space is used for the segmentation technique. Comparative analysis in terms of segmentation efficiency and convergence rate is performed between the conventional FCM and the modified FCM. Experimental results show superior results for the modified FCM algorithm in terms of the performance measures.

Fuzzy sets, rough sets are efficient tools to handle uncertainty and vagueness in the medical images and are widely used for medical image segmentation. Soft sets are a new mathematical approach to uncertainty and vagueness. In this paper, a hybrid segmentation algorithm based on soft sets namely soft fuzzy rough c-means is proposed to extract the white matter, gray matter and the cerebro spinal fluid from MR brain image with bias field correction. In this algorithm, soft fuzzy rough approximations are applied to obtain the rough regions of image. These approximations are free from defining thresholds, weight parameters and are less complex compared to the existing rough set based algorithms. Soft sets use similarity coefficients to find the similarity of the clusters formed in present and previous step. The proposed algorithm does not involve any negative region, hence all the pixels participate in clustering avoiding clustering mistakes. Also, the histogram based centroids choose the centroids close to the ground truth that in turn effect the definition of approximations, standardizing the clusters. The proposed algorithm evaluated through simulation, compared it with existing k-means, rough k-means, fuzzy c-means and other hybrid algorithms. The soft fuzzy rough c-means algorithm outperforms the considered algorithms in all analyzed scenarios even in extracting the stone from the brain tissue.

III. PROPOSED SYSTEM

Kidney stones are a common complaint worldwide, causing many people to admit to emergency rooms with severe pain. Various imaging techniques are used for the diagnosis of kidney stone disease. Specialists are needed for the interpretation and full diagnosis of these images. Computer-aided diagnosis systems are the practical approaches that can be used as auxiliary tools to assist the clinicians in their diagnosis. In this study, an automated detection of kidney stone (having stone/not) using coronal computed tomography (CT) images is proposed with deep learning (DL) technique which has recently made significant progress in the field of artificial intelligence. In this proposed system proposes to spot the Stone from CT scan medical images using image classification system. The Kidney CT scan is taken and its noises are removed using filters and then applied spatial Fuzzy C means Clustering algorithm for the segmentation of CT scan Kidney images. We use resnet model for classification of the kidney stone.

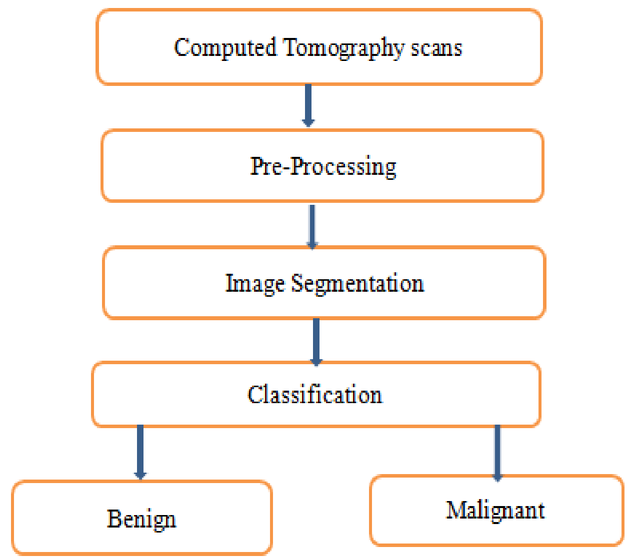


Fig 1 Block Diagram

This project includes simple segmentation and classification algorithms for kidney stone using Computed Tomography images. Stones are of different types having different characteristics and also have different treatment. It becomes very important to detect the stone and classify it at the early stage so that appropriate treatment can be planned. This CT scans are visually examined by the physician for detection and diagnosis of kidney stone. However this method lacks accuracy and detection of size of the stone. So to overcome this proposed technique, which extracts the stone part from the kidney, further on which feature extraction method is performed for extracting certain features and the type of stone i.e. malignant or benign is displayed by using simple classifiers

Fuzzy C-Means Clustering Algorithm

In FCM, it is possible for a data sample to belong to multiple clusters at the same time. The similarity is indicated by the membership value. In FCM a data sample is assigned with a membership value based on its similarity with the cluster center. The membership values are between 0 to 1 and more the similarity, higher the membership value.

When the algorithm converges, all kinds of clustering centers and samples are obtained. For each kind of membership degree, the fuzzy clustering division is completed Finally, the results of the fuzzy clustering are de-fuzzified and the fuzzy clustering is transformed into deterministic classification.

Data Acquisition

The dataset is collected from The Cancer Imaging Archive (TCIA), a large publicly available archive of medical cancer images. DICOM is TCIA's primary image storage file format. It contains the most commonly used imaging techniques such as PET, CT, MR, etc. and the use of purely real data set collected from Medical laboratory which contains CT images of kidney cancer patients. Computed tomography scan is a non-conspicuous indicative imaging system which uses X-ray and computer technology to create flat or pivotal images of the entire body (often called slices). A CT check shows pictures of any and every part, such as internal organs, muscles, fat and major organs. CT scans are often more detailed and specific than normal X-rays.

CT scans of most of the kidneys are extremely useful in the inspection of either kidney to locate conditions, such as stones or various sores, obstructive conditions, such as kidney stones, innate abnormalities, polycystic kidney disease, solvent compilation all around the kidneys and abscesses.

Preprocessing

Almost in every pattern recognition system, it is an appealing step to enhance its performance and eliminate variations and generate an even more consistent set of data. This method involves recognizing the major source of noise with a proper filtering technique and eliminating the noise.

Anisotropic diffusion filter produces better noise reduction results and preserves edge without much loss of information. A novel fast oriented anisotropic diffusion filter which yields the best image performance metrics. The memory based anisotropic diffusion filter that reduces progressive loss of information in US images.

Image Segmentation

Image segmentation is defined as the image divisions into regions that are relevant to a particular task; it is a problem of labeling. Segmentation is the main step to analyze and interpret images. Detecting and classifying the stone at an early stage is most essential in order to plan appropriate treatment. The doctor visually examines these CT scans for kidney stone detection and diagnosis. Therefore, the segmentation method was proposed to overcome this, which extracts the part of the stone from the kidney.

Fuzzy clustering algorithm is one of the most important branches of clustering algorithm . Different from traditional clustering methods, it divides each object to be classified into one category or another. Fuzzy clustering algorithm uses fuzzy method to cluster, and gives the degree of uncertainty of sample classification, which conforms to the nature of things in the real world. It can reect the real world more objectively.

Fuzzy C-means Clustering (FCM) algorithm is one of the most classical fuzzy clustering algorithms, which searches for the optimal extremes through repeated iterations. Because the Euclidean distance is used as the distance measure in the objective function of FCM algorithm, the samples close to each other in the sample space will be clustered together.

Clustering analysis largely depends on the distribution of data sets. If the sample space itself is linear ``agglomerative", FCM can achieve good clustering effect; but if the sample space is non-linear ``agglomerative", the clustering effect of this kind of method will be unsatisfactory. In document, the kernel function theory is introduced into cluster analysis, and a clustering method based on kernel function is proposed. In practical application, according to statistical theory, a function can be regarded as a kernel function as long as it satisfies Mercer condition. Kernel-fuzzy C- means clustering algorithm maps the samples in the original space to the high- dimensional feature space through the kernel function, and then carries out FCM clustering. This can make the linearly inseparable samples in the original space become linearly separable, and overcome the disadvantage that FCM is not suitable for the non-linear data distribution to a certain extent.

The segmentation of the key areas, namely gray matter and white matter, is not clear, and white matter is divided into several discontinuous regions. With this algorithm, white matter can be divided into a connected whole region, so that white matter and gray matter and gray matter have a clearer segmentation boundary. The cluster number $C = 5$ was selected. Through the unified image processing, the image is converted into $512*512$, the value of the fuzzy factor is chosen as $P=2$, three different iteration stop thresholds are selected, and the maximum iteration times are set to 300. In FCM algorithm, the misadvised soft tissues are segmented accurately, and the skeleton and soft tissues are clearly segmented from the background. And the white matters, gray matters and cerebrospinal fluid are obvious in the segment results.

Classification

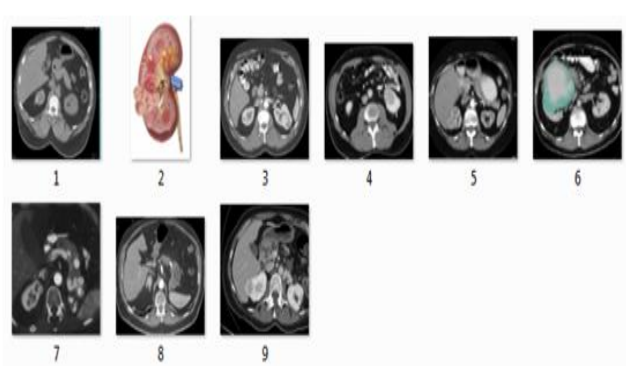
Deep residual networks like the popular ResNet-50 model are a convolutional neural network (CNN) that is 50 layers deep. A Residual Neural Network (ResNet) is an Artificial Neural Network (ANN) of a kind that stacks residual blocks on top of each other to form a network. ResNet has many variants that run on the same concept but have different numbers of layers. Resnet50 is used to denote the variant that can work with 50 neural network layers.

In this case, the building block was modified into a bottleneck design due to concerns over the time taken to train the layers. This used a stack of 3 layers instead of the earlier 2. Therefore, each of the 2-layer blocks in Resnet34 was replaced with a 3-layer bottleneck block, forming the Resnet 50 architecture. This has much higher accuracy than the 34-layer ResNet model.

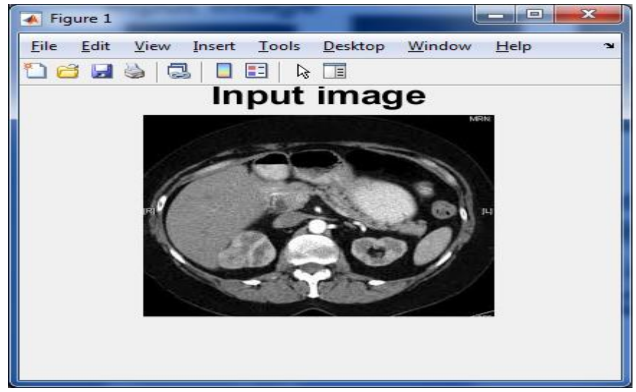
Residual network or ResNet was a major innovation that has changed the training of deep convolutional neural networks for tasks related to computer vision. While the original Resnet had 34 layers and used 2-layer blocks, other advanced variants such as the Resnet50 made the use of 3-layer bottleneck blocks to ensure improved accuracy and lesser training time.

ResNet-50 is a convolutional neural network that is 50 layers deep. ResNet, short for Residual Networks is a classic neural network used as a backbone for many computer vision tasks. The segmentation image value is given to the input of ResNet-50. The ResNet-50 classification is performed to find the type of stone (Malignant or Benign).

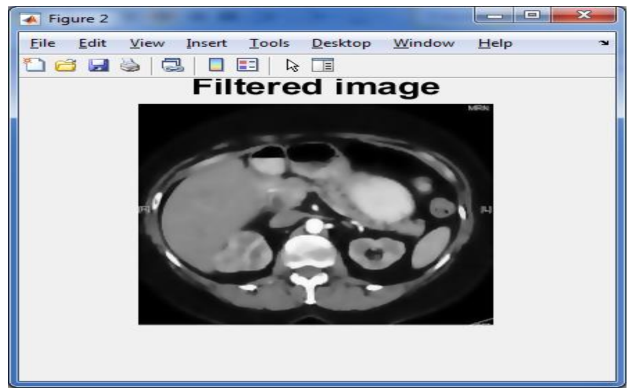
IV. SCREEN SHOTS



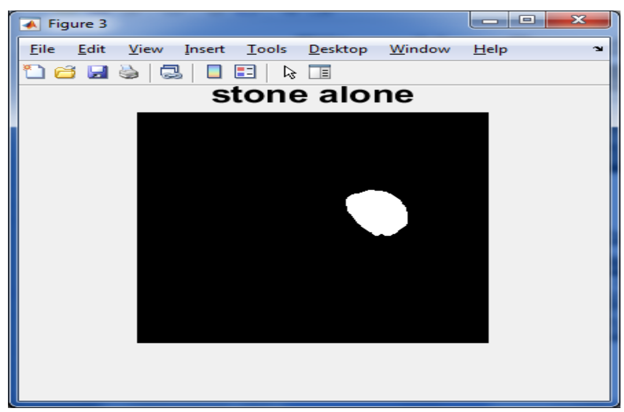
Input Image Dataset



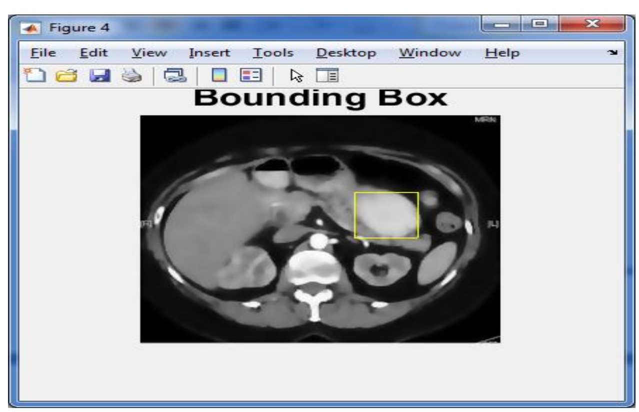
Input Image



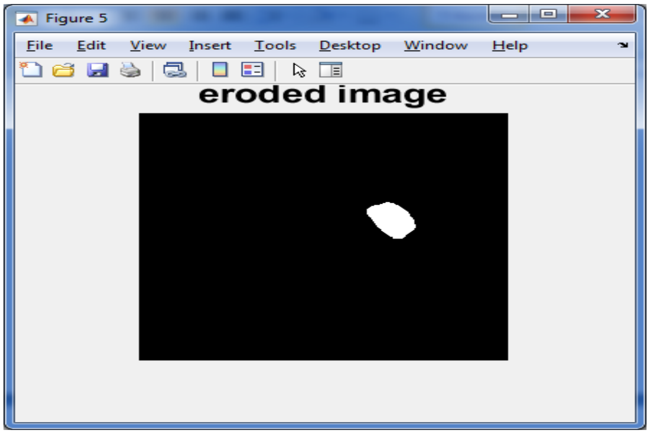
Filtered Image



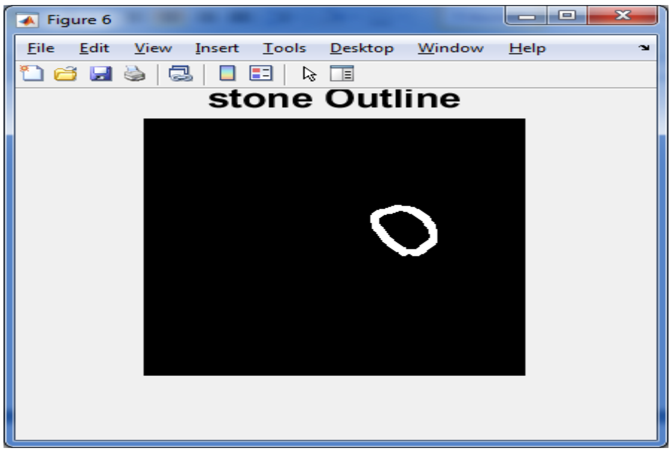
Stone Alone



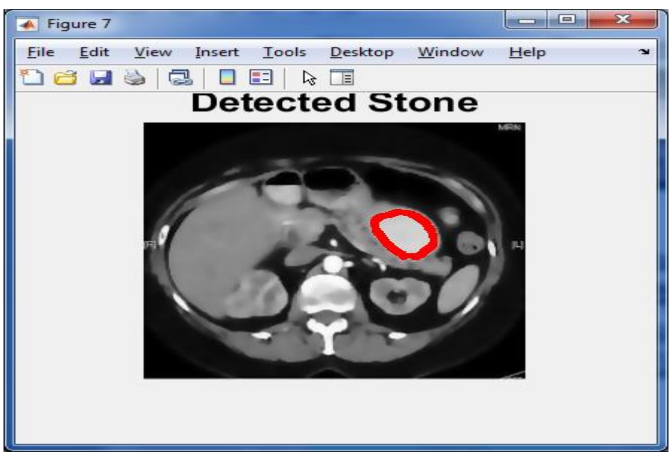
Bounding Box



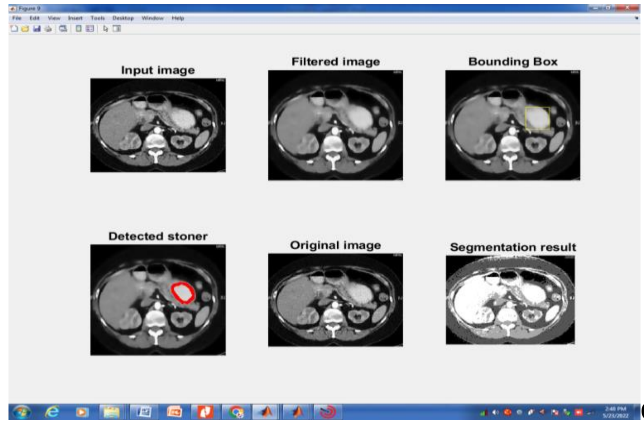
Eroded Image



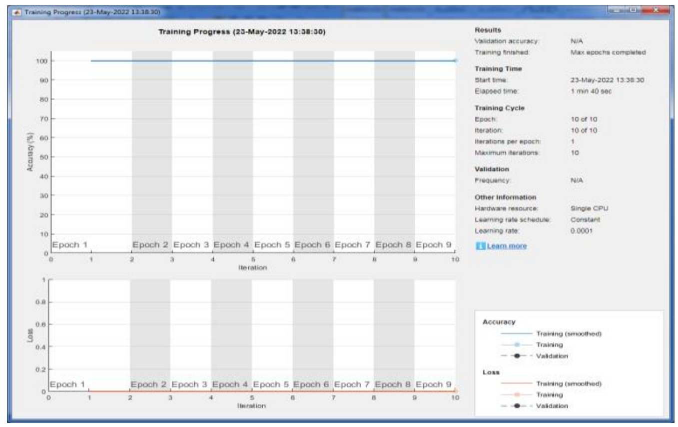
Stone Outline



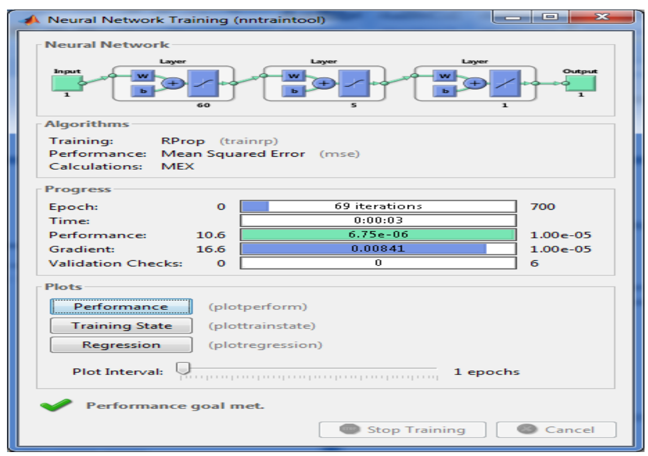
Detected Stone



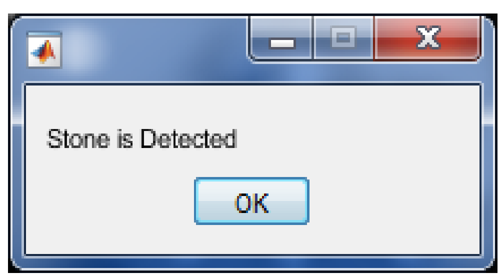
Ov er all Process



Classification Result



ReNnet Classifier



Dialogue Box

V. CONCLUSION

Thus, to remain healthy, cells grow and divide in orderly fashion. When cell growth becomes uncontrollable the extra mass of cell transforms into stone. CT scans and MRI are used for identification of stone. A novel kidney segmentation method for Computed Tomography patient data with kidney cancer is proposed. The segmentation process is based on Fuzzy C-Means Clustering Algorithm. It becomes very important to detect the stone and classify it at the early stage so that appropriate treatment can be planned. This CT scans are visually examined by the physician for detection and diagnosis of kidney stone. However this method lacks accuracy and detection of size of the stone. So to overcome this, a computer aided segmentation technique has been proposed, which extracts the stone part from the kidney, further on which feature extraction method is performed for extracting certain features using ResNet50 and for classification also performed to find the type of stone (Malignant or Benign).

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