

TUMOUR DETECTION USING INTERACTIVE IMAGE SEGMENTATION AND CNN

Submitted in partial fulfillment of the requirements for
the award of
Bachelor of engineering degree in Computer Science and Engineering
by

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING**

SATHYABAMA
INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
Accredited with Grade "A" by NAAC

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APRIL 2022



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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Nayanika Saha (38110359)** and **Anamika Shil (38110032)** who carried out the project entitled “**TUMOUR DETECTION USING INTERACTIVE IMAGE SEGMENTATION USING CNN**” under our supervision from **November 2021 to April 2022**.

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DECLARATION

We, **Nayanika Saha (38110359) and Anamika Shil (38110032)** here by declare that the project Report entitled “TUMOUR DETECTEION USING INTERACTIVE IMAGE SEGMENTATION AND **CNN**” done by me under the guidance of **Dr. S. Gowri** at Sathyabama Institute of Science and Technology is submitted in partial fulfillment of the requirements for the award of **Bachelor of Engineering Degree in Computer Science and Engineering.**

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SIGNATURE OF THE CANDIDATE

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ABSTRACT

DEEP learning with convolution neural networks (CNNs) has achieved state-of-the-art performance for automated medical image segmentation. However, automatic segmentation methods have not demonstrated sufficiently accurate and robust results for clinical use due to the inherent challenges of medical images, such as poor image quality, different imaging and segmentation protocols and variations among patients. Interactive segmentation often requires image specific learning to deal with large context variations among different images but current CNNs are not adaptive to different test images, as parameters of the model are learned from training images and then fixed in the testing stage without image specific adaptation. The Proposed system focus on interactive tumor segmentation of medical image sequences using deep neural network. The proposed work utilizes pattern based classification using neural network function. Adaptive Hierarchical motion segmentation is designed in the proposed area.

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Liver cancer remains associated with a high mortality rate, in part related to initial diagnosis at an advanced stage of disease. Prospects can be significantly improved by earlier treatment beginning, and analysis of CT images is a main diagnostic tool for early detection of liver tumors. Manual inspection and segmentation is a labor and time intensive process yielding relatively imprecise results in many cases. Thus, there is significant interest in developing automated strategies to support the early detection of lesions. Due to complex backgrounds, significant variations in location, shape and intensity across different patients, both, the automated liver segmentation and the further detection of tumors, remain challenging tasks.

1.2 TYPES OF IMAGE SCAN

Due to its detoxification function the liver one of the essential organs in the human body.

Radiologists and oncologists analyze computed tomography (CT) or magnetic resonance images (MRI) to study livers anomalies in shape and texture. These anomalies are important biomarkers for initial disease diagnosis and progression in both primary and secondary hepatic tumor disease. Often primary tumors of the abdomen such as breast, colon and pancreas cancer spread metastases to the liver during the course of disease. Therefore, the liver and its lesions are routinely analyzed in primary tumor staging. The RECIST protocol, which states to measure the diameter of the largest target lesion, has become clinical reference standard in tumor staging of liver cancer. From a global perspective primary liver cancer is the second most common cause of cancer death and is the sixth most frequent cancer. Computed tomography (CT) is the most commonly used image modality by radiologists and oncologists for liver lesion evaluation and staging. Furthermore, segmenting malignant liver tissues is important for cancer diagnosis, treatment, planning, and tracking treatment response. In addition, liver and tumor segmentation is also a prerequisite or a key asset for many treatment options such as thermal percutaneous ablation, percutaneous ethanol injection, radiotherapy

surgical resection and arterial embolization. However diagnostic imagery is expensive, very time-consuming, and poorly reproducible and its segmentations show operator-dependent results.

Since tumor volume is a better predictor than diameter, according to the Response Evaluation Criteria in Solid Tumor (RECIST), automatic segmentation is the most desirable goal.

However, a fully-automated segmentation of liver and its lesion remains still an open problem because different acquisition protocols, differing contrast-agents, varying levels of contrast enhancements and dissimilar scanner resolutions lead to unpredictable intensity differences between liver and lesion tissue. Many different types of lesions and especially tumor sub-types can occur in affected livers. Thus, these different types of tumors with varying contrast levels (hyper-/hypo-intense tumors) form obstacles to overcome. Modern methods struggle with abnormalities in tissues (such as after surgical resection of metastasis) or the size, shape and varying number of lesions.

Liver cancer was the second most common cause of cancer-induced deaths in 2015 according to the World Health Organization. Hepatocellular carcinoma (HCC) is the most common type of primary liver cancer which is the sixth most prevalent cancer. In addition, the liver is also a common site for secondary tumors. Liver therapy planning procedures would profit from an accurate and fast lesion segmentation that allows for subsequent determination of volume- and texture-based information. Moreover, having a standardized and automatic segmentation method would facilitate more reliable therapy response classification.

Liver tumors show a high variability in their shape, appearance and localization. They can be either hypodense (appearing darker than the surrounding healthy liver parenchyma) or hyperdense and can additionally have a rim due to the contrast agent accumulation, calcification or necrosis. The individual appearance depends on lesion type, state, imaging (equipment, settings, contrast method and timing), and can vary substantially from patient to patient. This high variability makes liver lesion segmentation a challenging task in practice.

1.3 INTRODUCTION TO IMAGE PROCESSING

Image Processing is a method to enhance raw images received from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-to-day life for various applications. Various techniques have been developed in Image Processing during the last four to five decades. Most of the techniques are developed for enhancing images obtained from unmanned spacecrafts, space probes and military reconnaissance flights. Image Processing systems are becoming popular due to easy availability of powerful personnel computers, large size memory devices, graphics software's etc. Image processing is a physical process used to convert an image signal into a physical image. The image signal can be either digital or analog. The actual output itself can be an actual physical image or the characteristics of an image.

Image processing is photography. In this process, an image is captured or scans using a camera to create a digital or analog image. In order to produce a physical picture, the image is processed using the appropriate technology based on the input source type. In digital photography, the image is stored as a computer file. This file is translated using photographic software to generate an actual image. The colors, shading, and nuances are all captured at the time the photograph is taken the software translates this information into an image. When creating images using analog photography, the image is burned into a film using a chemical reaction triggered by controlled exposure to light. The image is processed in a darkroom, using special chemicals to create the actual image.

CHAPTER 2

LITERATURE SURVEY

[1] Title: FRACTALNET: ULTRA-DEEP NEURAL NETWORKS WITHOUT RESIDUALS

Author Name: Gustav Larsson, Michael Maire

Year Of Publication: 2017

We introduce a design strategy for neural network macro-architecture based on self similarity. Repeated application of a simple expansion rule generates deep networks whose structural layouts are precisely truncated fractals. These networks contain interacting sub paths of different lengths, but do not include any pass-through or residual connections; every internal signal is transformed by a filter and nonlinearity before being seen by subsequent layers. In experiments, fractal networks match the excellent performance of standard residual networks on both CIFAR and Image Net classification tasks, thereby demonstrating that residual representations may not be fundamental to the success of extremely deep convolution neural networks. Rather, the key may be the ability to transition, during training, from effectively shallow to deep. We note similarities with student-teacher behavior and develop drop-path, a natural extension of dropout, to regularize co-adaptation of sub paths in fractal architectures. Such regularization allows extraction of high performance fixed-depth sub networks. Additionally, fractal networks exhibit an anytime property: shallow sub networks provide a quick answer, while deeper sub networks, with higher latency, provide a more accurate answer.

[2] Title: The Liver Tumor Segmentation Benchmark (LiTS)

Author Name: Patrick Bilic^{1a}, Patrick Ferdinand Christ¹

Year Of Publication: 2019

In this work, we report the set-up and results of the Liver Tumor Segmentation Benchmark (LiTS) organized in conjunction with the IEEE International Symposium on Biomedical Imaging (ISBI) 2017 and International Conference On Medical Image Computing & Computer Assisted Intervention (MICCAI) 2017. Twenty-four valid state-of-the-art liver and liver tumor

segmentation algorithms were applied to a set of 131 computed tomography (CT) volumes with different types of tumor contrast levels (hyper-/hypo-intense), abnormalities in tissues (metastasectomie) size and varying amount of lesions. The submitted algorithms have been tested on 70 undisclosed volumes. The dataset is created in collaboration with seven hospitals and research institutions and manually blind reviewed by independent three radiologists. We found that not a single algorithm performed best for liver and tumors. The best liver segmentation algorithm achieved a Dice score of 0.96(MICCAI) whereas for tumor segmentation the best algorithm evaluated at 0.67(ISBI) and 0.70(MICCAI). The LiTS image data and manual annotations continue to be publicly available through an online evaluation system as an ongoing benchmarking resource.

[3] Title: Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks

Author Name: Shaoqing Ren_ Kaiming He Ross Girshick Jian Sun

Year Of Publication: 2016

State-of-the-art object detection networks depend on region proposal algorithms to hypothesize object locations. Advances like SPPnet [7] and Fast R-CNN [5] have reduced the running time of these detection networks, exposing region proposal computation as a bottleneck. In this work, we introduce a Region ProposaNetwork (RPN) that shares full-image convolution features with the detection network, thus enabling nearly cost-free region proposals. An RPN is a Fully-convolution network that simultaneously predicts object bounds and objectless scores at each position. RPNs are trained end-to-end to generate high quality region proposals, which are used by Fast R-CNN for detection. With a simple alternating optimization, RPN and Fast R-CNN can be trained to share convolution features. For the very deep VGG-16 model [19], our detection system has a frame rate of 5fps (including all steps) on a GPU, while achieving state-of-the-art object detection accuracy on PASCAL VOC 2007 (73.2% mAP) and 2012 (70.4% mAP) using 300 proposals per image

[4] Title: Detection-aided liver lesion segmentation using deep learning

Author Name: Anonymous

Year Of Publication: 2017

A fully automatic technique for segmenting the liver and localizing its unhealthy 2 tissues is a convenient tool in order to diagnose hepatic diseases and assess the 3 response to the according treatments. In this work we propose a method to segment 4 the liver and its lesions from Computed Tomography (CT) scans using Convolution Neural Networks (CNNs) that have proven good results in a variety of 6 computer vision tasks, including medical imaging. The network that segments the 7 lesions consists of a cascaded architecture, which first focuses on the region of 8 the liver in order to segment the lesions on it. Moreover, we train a detector to 9 localize the lesions, and mask the results of the segmentation network with the 10 positive detections. The segmentation architecture is based on DRIU [8], a Fully 11 Convolution Network (FCN) with side outputs that work on feature maps of 12 different resolutions, to finally benefit from the multi-scale information learned by 13 different stages of the network. The main contribution of this work is the use of 14 a detector to localize the lesions, which we show to be beneficial to remove false 15 positives triggered by the segmentation network.

[5] Title: Automatic Liver and Lesion Segmentation in CT Using Cascaded Fully Convolution Neural Networks and 3D Conditional Random Fields

Author Name: Patrick Ferdinand Christ¹, Mohamed Ezzeldin A

Year Of Publication: 2017

Automatic segmentation of the liver and its lesion is an important step towards deriving quantitative biomarkers for accurate clinical diagnosis and computer-aided decision support systems.

This paper presents a method to automatically segment liver and lesions in CT abdomen images using cascaded fully convolution neural networks (CFCNs) and dense 3D conditional random fields (CRFs). We train and cascade two FCNs for a combined segmentation of the liver and its lesions. In the first step, we train a FCN to segment the liver as ROI input for a second FCN. The second FCN solely segments lesions from the predicted liver ROIs of step 1. The segmentations of the CFCN using a dense 3D CRF that accounts for both spatial coherence and appearance. CFCN models were trained in a 2-fold cross-validation on the

abdominal CT dataset 3DIRCAD comprising 15 hepatic tumor volumes. Our results show that CFCN-based semantic liver and lesion segmentation achieves Dice scores over 94% for liver with computation times below 100s per volume. We experimentally demonstrate the robustness of the proposed method as a decision support system with a high accuracy and speed for usage in daily clinical routine.

CHAPTER 3

METHODOLOGY

3.1 EXISTING SYSTEM

A review based model is developed here. In the existing system we introduces the machine learning algorithms as applied to medical image analysis, focusing on convolution neural networks, and emphasizing clinical aspects of the field. The advantage of machine learning in an era of medical big data is that significant hierarchal relationships within the data can be discovered algorithmically without laborious hand-crafting of features. We cover key research areas and applications of medical image classification, localization, detection, segmentation, and registration. We conclude by discussing research obstacles, emerging trends, and possible future directions.

3.2 PROPOSED SYSTEM

In the proposed system an enhanced interactive model is designed. An interactive sequence of images is fetched from the scanner database. Those images are pre processed and further segmented for the required feature. The segmented data is further classified through a motion based active contour segmentations in which the image sequence if validated frame by frame for the set of duration. Here the threshold required for segmenting adjusts itself according to the segmented area and position. The result image will compared with the dataset images and it will display whether it is benign or malignant.

3.3 MODULE DESCRIPTION

3.3.1 Preprocessing

If the input images are color images means we are convert to gray scale from that color images. In the complement of a binary image, zeros become ones and ones become zeros; black and white are reversed. In the output image, dark areas become lighter and light areas become darker. Images may have different types of noise. In image enhancement, the goal is to accentuate certain image

features for subsequent analysis or for image display. Examples include contrast and edge enhancement, pseudo-coloring, noise filtering, sharpening, and magnifying. Image enhancement is useful in feature extraction, image analysis and an image display. The median filter is used in order to remove the noise from the image. Median filtering is a nonlinear operation often used in image processing to reduce salt and pepper noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges

3.3.2 Segmentation

The image features like color, weight, and depth and pixel information to apply before the classifier. Here we used the Active Contour segmentation algorithm is used in order to segment the portion of defected areas. Image segmentation is typically used to locate objects and boundaries in images. More precisely image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. As image segmentation methods, there are two kinds of active contour models according to the force evolving the contours: edge- and region-based. Edge based active contours apply an edge detector, typically based on the image gradient, to locate the boundaries of sub-regions and to draw the contours to the detected boundaries. Edge-based approaches are closely connected to the edge-based segmentation. Region based active contours apply the statistical information of image intensity inside each subset instead of searching geometrical boundaries. Region-based approaches are also closely connected to the region-based segmentation.

3.3.3 Back Propagation

This module is used to establish the back propagation neural network concept for training the image and testing the image with the help of weight estimating classifier. The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units. The activity of the input units represents the raw information that is fed into the network. The activity

of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.

The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units. This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents. The result image will be compared with the dataset images and it will display whether it is normal or abnormal.

3.4 SEGMENTATION

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images. More precisely image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture.

There are two major approaches in image segmentation: edge- and region-based. Edge based segmentation partitions an image based on discontinuities with sub-regions, while regionbased segmentation does the similar function based on the uniformity of a desired property within a sub-region.

3.5 ACTIVE COUNTERS

The method of active contours has become quite popular for a range of applications, mainly image segmentation and motion tracking, through the last decade. This methodology is based upon the use of deformable contours which match to various object shapes and motions. This section provides a theoretical setting of active contours and an indication of existing active contour methods. There are two main approaches in active contours based on the mathematic implementation: snakes and level sets. Snakes explicitly shift predefined snake

points based on an energy minimization method, while level set approaches move contours completely as a particular level of a function.

As image segmentation methods, there are two kinds of active contour models according to the force evolving the contours: edge- and region-based. Edge based active contours apply an edge detector, typically based on the image gradient, to locate the boundaries of sub-regions and to draw the contours to the detected boundaries. Edge-based approaches are closely connected to the edgebased segmentation. Region based active contours apply the statistical information of image intensity inside each subset instead of searching geometrical boundaries. Region-based approaches are also closely connected to the region-based segmentation.

3.5.1 Edge Based Counters

Edge-based active contours are strongly connected to the edge-based segmentation. Most edge based active contour models consist of two parts: the regularity part, which determines the form of contours, and the edge recognition part, which attracts the contour towards the boundaries. Edgebased active contour models have a little disadvantages compared to the region-based active contour models, discussed in the next section. Because of the constant term, edge based active contour models evolve the contour towards only one way, each inside or outside. Therefore, an primary contour must be placed completely inside or outside of ROI, and some level of a previous knowledge is still necessary .Also, edge-based active contours inherit a few disadvantages of the edge-based segmentation methods due to the parallel method used. Since both edge-based segmentation and edge-based active contours rely on the image gradient process, edge-based active contours may omit the blurry boundaries, and they are sensitive to local minima or noise as edge-based segmentation does. Gradient vector flow quick geodesic dynamic contours proposed by Paragios replaced the border detection (boundary attraction) word with gradient vector field that refers to a spatial diffusion of the boundary information and guides the propagation to the object boundaries from equally sides, to give extra freedom from the restriction of first contour position.

3.5.2 Region-Based Active Counters

Most region-based active contour models consist of two parts: the regularity part, which determines the smooth form of contours, and the energy minimization

part, which searches for equality of a preferred feature within a subset. A good characteristic of region-based active contours is that the first contours can be situated anywhere in the image as region-based segmentation relies on the global energy minimization rather than local energy minimization. Therefore, less previous knowledge is required than edge-based active contours. Although usual region-based active contours partition an image into several sub regions, those several regions belong to only two subsets: both the inside or the outside of contours. Chan and Vese proposed multi-phase active contour model which increases the amount of subsets that active contours can locate simultaneously. Multiple active contours evolve independently based on the piecewise-constant model or the piecewise-smooth model, and multiple subsets are defined by a set of disjoint combination of the level set functions. Due to the global energy minimization; region based active contours usually do not have any restriction on the placement of first contours. That is, region-based active contour can detect interior boundaries regardless of the position of initial contour. That is, region-based active contour can detect inner boundaries regardless of the position of initial contours. The use of pre-defined initial contours provides a method of independent segmentation. Also, they are less responsive to local minima or noise than edge-based active contours. However, due to the supposition of uniform image intensity, most methods are relevant only to images where each subset is stand for able by a simple expression, e.g. single Gaussian distribution or a constant. If a subset, i.e. class, consists of multiple distinguishing sub-classes, these methods would produce over-segmented or under-segmented results. We propose novel region-based active contour models which produce better results using multivariate mixture density functions.

3.6 NEURAL NETWORK

A Neural Network (NN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. NNs, like people, learn by example. An NN is configured for a specific application, such as pattern recognition or data classification, through a learning

process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons.

3.6.1 Historical Background

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras.

Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers. These pioneers were able to develop convincing technology which surpassed the limitations identified by Minsky and Papert. Minsky and Papert, published a book (in 1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis. Currently, the neural network field enjoys a resurgence of interest and a corresponding increase in funding

3.6.2 Basics Of Neural Networks

Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is output as shown in the graphic below.

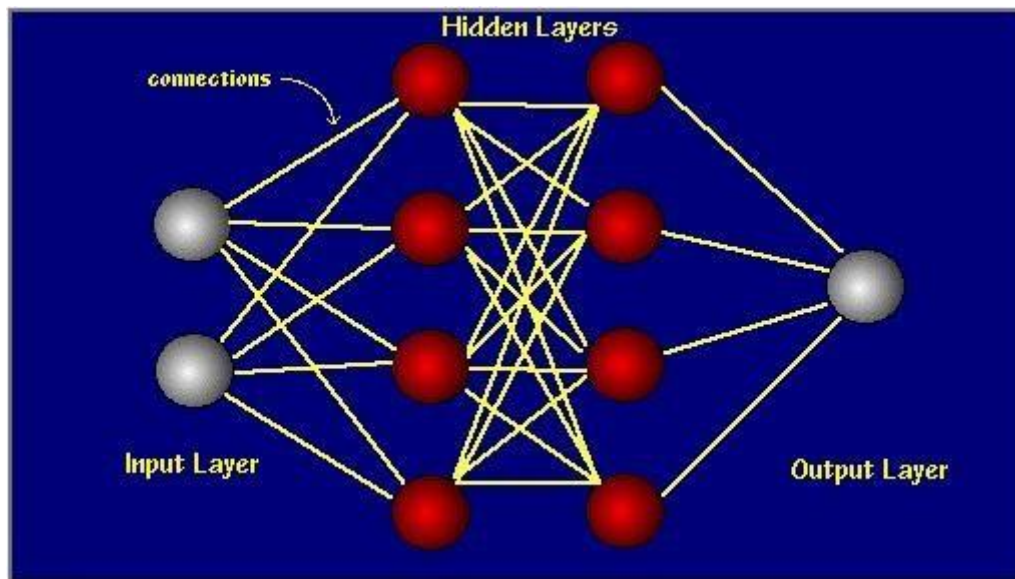


Fig. 3.1 : Neural network layers

Use Of Neural Networks

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations.

Other Advantages Include

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organization: An NN can create its own organization or representation of the information it receives during learning time.
3. Real Time Operation: NN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

3.6.3 Neural Networks Versus Conventional Computers

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Solve the

problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more unless the specific steps that the computer needs to follow are known the computer cannot useful if they could do things that we don't exactly know how to do.

Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem is to solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong is due to a software or hardware fault.

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks are more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency.

3.6.4 Network Layers

The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units.

The activity of the input units represents the raw information that is fed into the network.

The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.

The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents.

We also distinguish single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organizations. In multi-layer networks, units are often numbered by layer, instead of following a global numbering.

From image sequences are closely related to the field of closed range photogrammetric. In this field images are used to make precise measurements of three-dimensional objects from a number of images, often taken by calibrated cameras. The main difference is that in computer vision, the focus is not on accuracy, but instead on reliability and speed of calculation. In all these problems different kind of so called features can be used. The simplest feature is points that are easily detected in the sequence, such as corners or painted marks. Other types of features are lines and curves, which are easier to detect and track but more difficult to use in structure and motion algorithms. In order to use our computer vision routines these features must be detected in advance and the correspondence between different images must be established.

3.7 DIAGRAMS

3.7.1 System Design

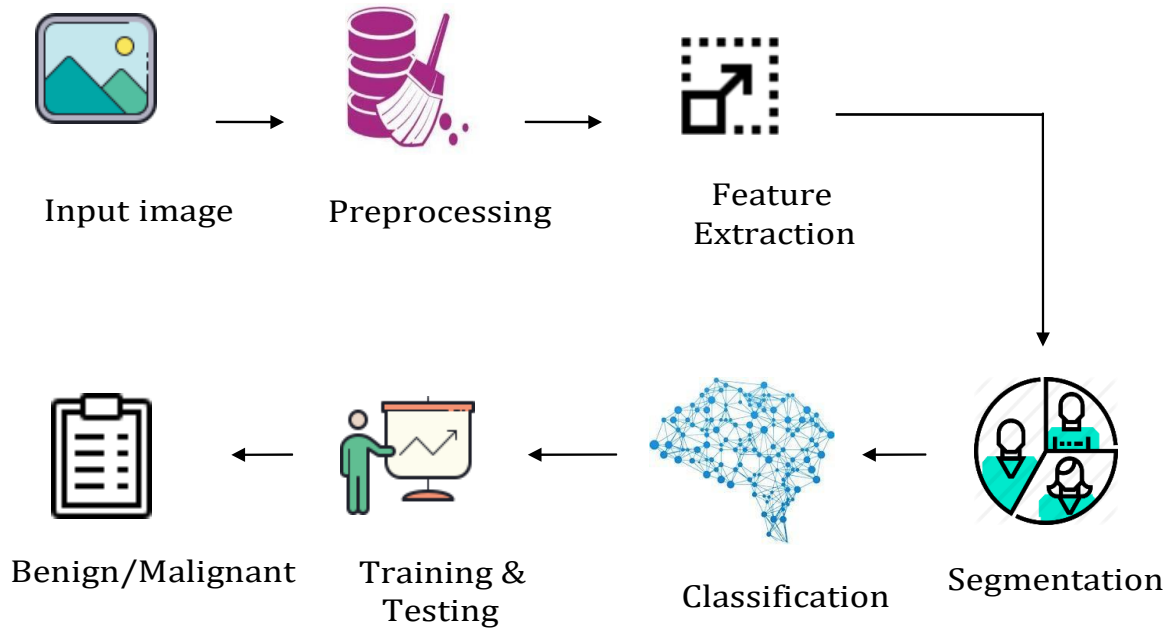


Fig. 3.2 : System Architecture

3.7.2 Activity Diagram

Activity diagram is a graphical representation of workflows of stepwise activities and actions with support for choice, iteration and concurrency. An activity diagram shows the overall flow of control.

The most important shape types:

- Rounded rectangles represent activities.
- Diamonds represent decisions.
- Bars represent the start or end of concurrent activities.
- A black circle represents the start of the workflow.
- An encircled circle represents the end of the work flow.

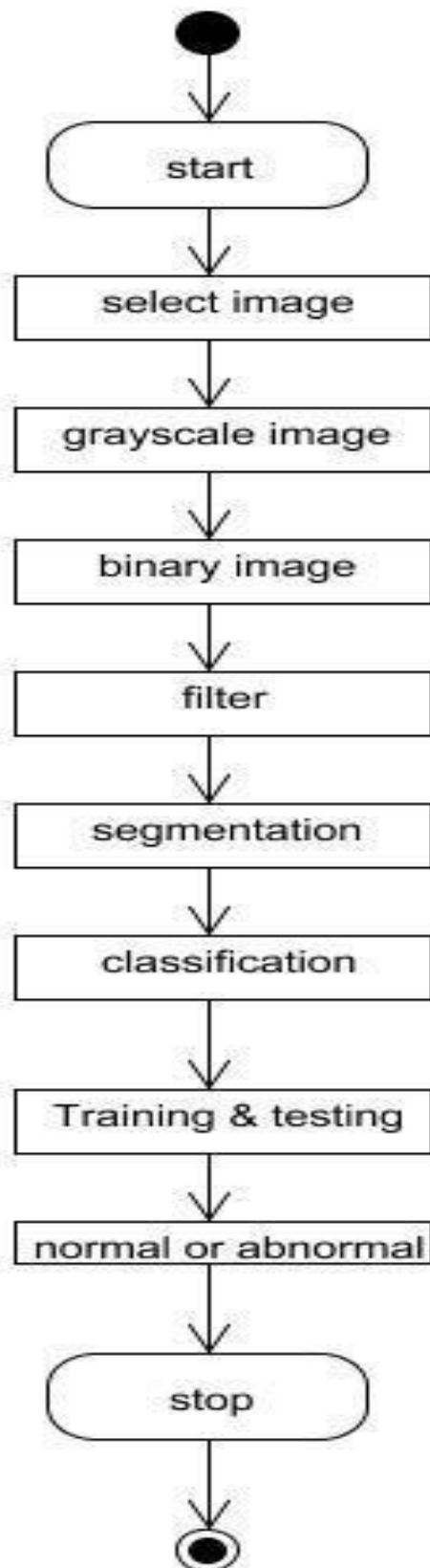


Fig. 3.3 : Activity Diagram

3.7.3 Sequence Diagram

A Sequence diagram is a kind of interaction diagram that shows how processes operate with one another and in what or

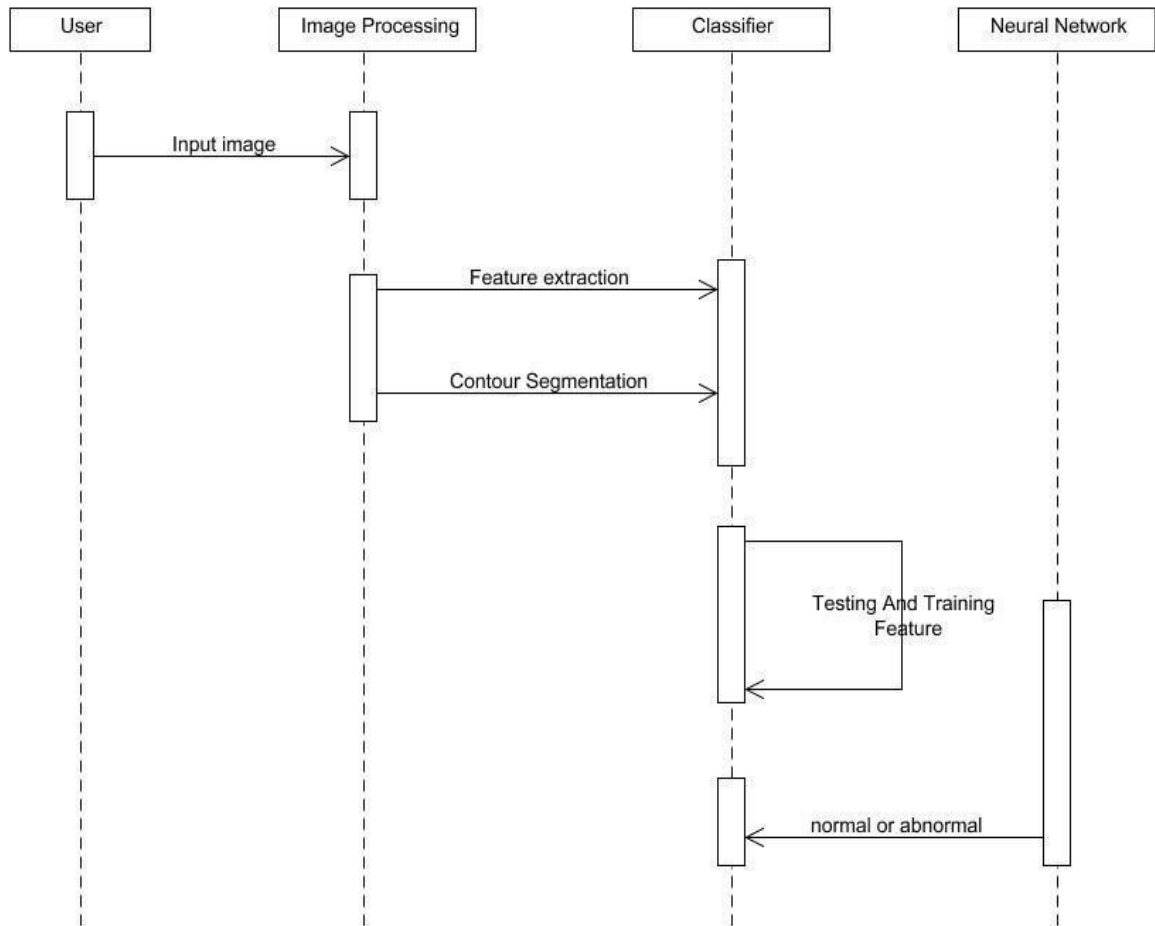


Fig.3.4 : Sequence Diagram

3.7.4 Use Case Diagram

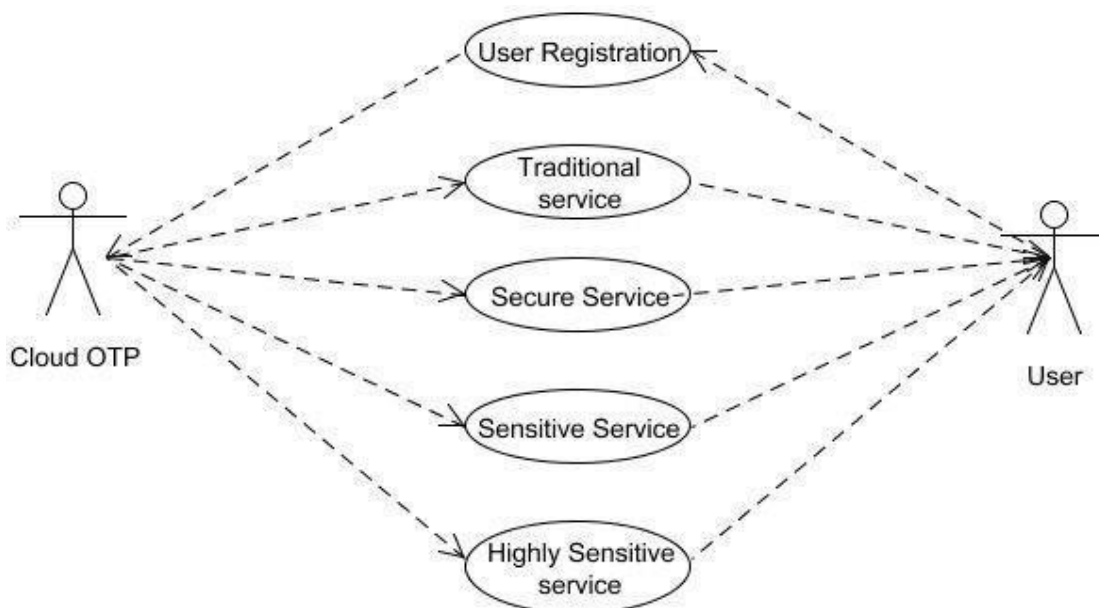
Unified Modeling Language (UML) is a standardized general-purpose modeling language in the field of software engineering. The standard is managed and was created by the Object Management Group. UML includes a set of graphic notation techniques to create visual models of software intensive systems. This language is used to specify, visualize, modify, construct and document the artifacts of an object oriented software intensive system under development.

A Use case Diagram is used to present a graphical overview of the functionality provided by a system in terms of actors, their goals and any dependencies between those use cases.

Use case diagram consists of two parts:

Use case: A use case describes a sequence of actions that provided something of measurable value to an actor and is drawn as a horizontal ellipse.

Actor: An actor is a person, organization or external system that plays a role in one or more interaction with the system.



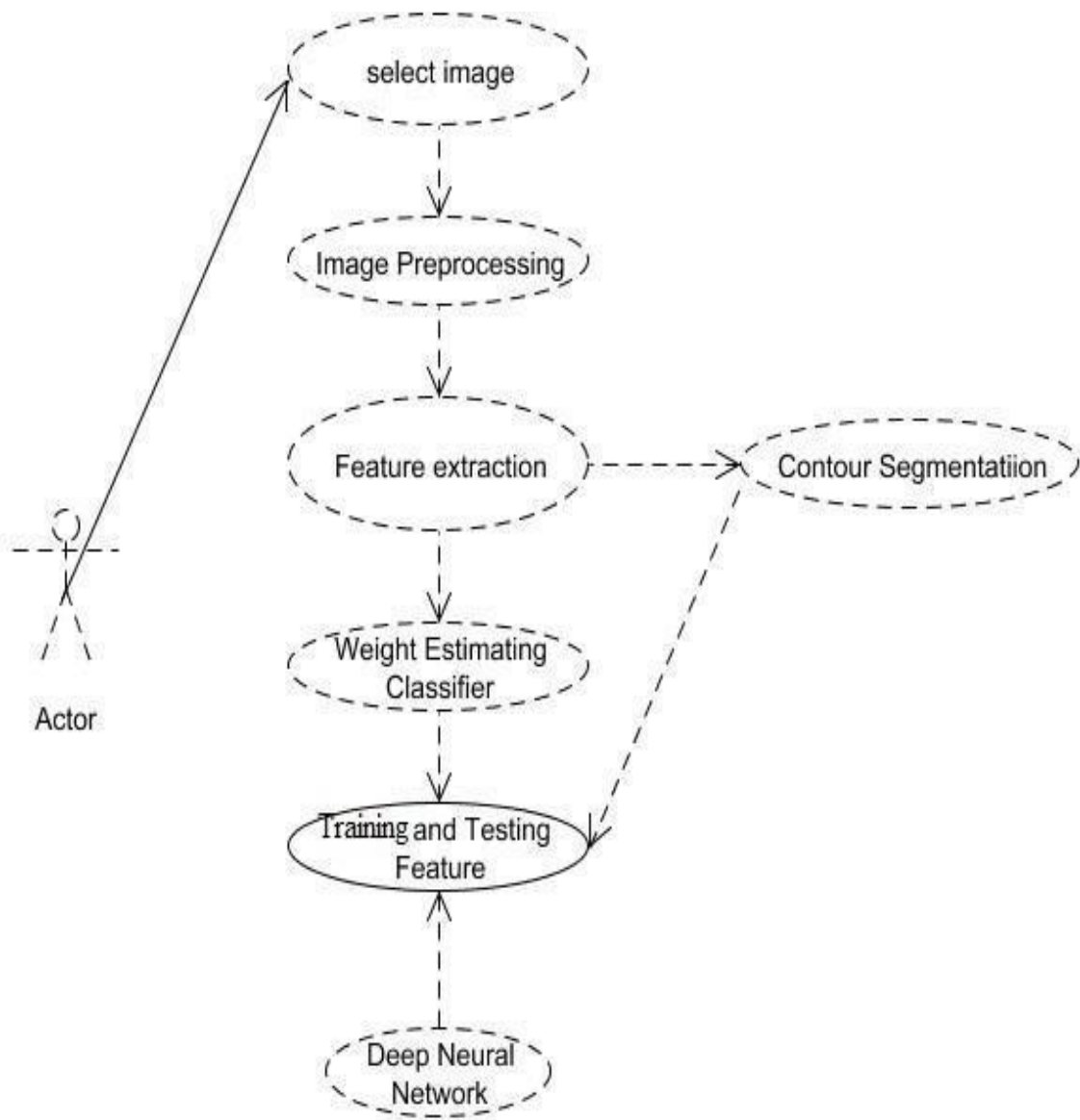
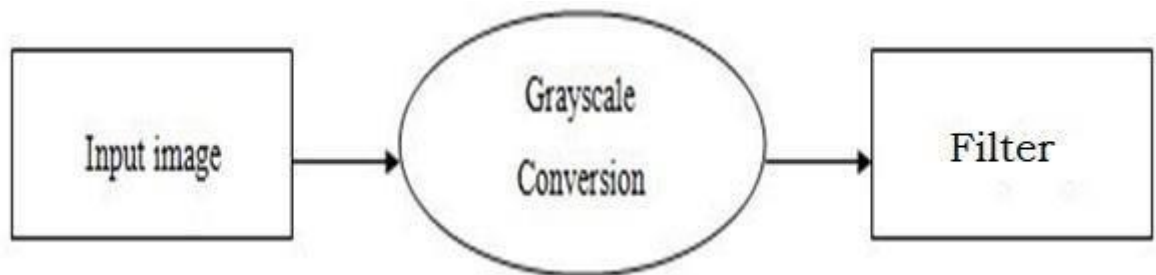


Fig. 3.5 : Use Case Diagram

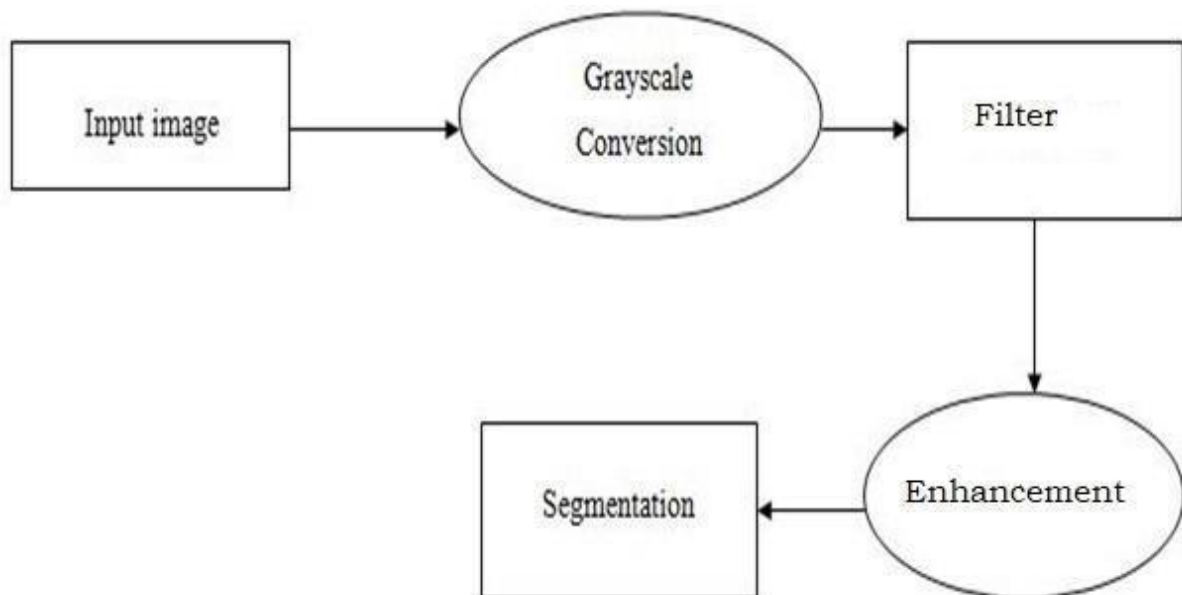
3.7.5 : ER Diagram

An Entity-relationship model (ER model) describes the structure of a database with the help of a diagram, which is known as Entity Relationship Diagram (ER Diagram). An ER model is a design or blueprint of a database that can later be implemented as a database. The main components of E-R model are: entity set and relationship set.

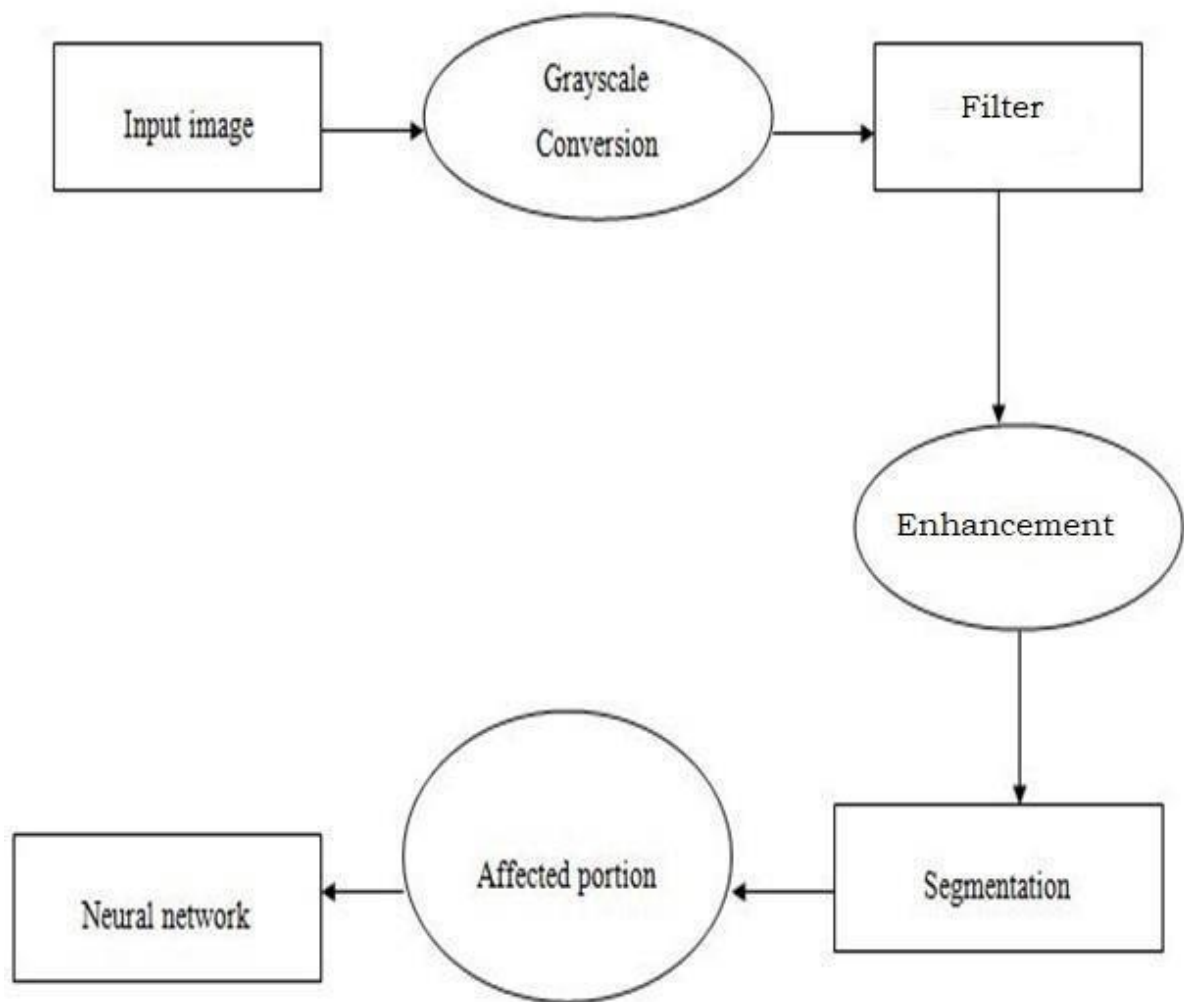
STEP 1



STEP 2



STEP 3



STEP 4

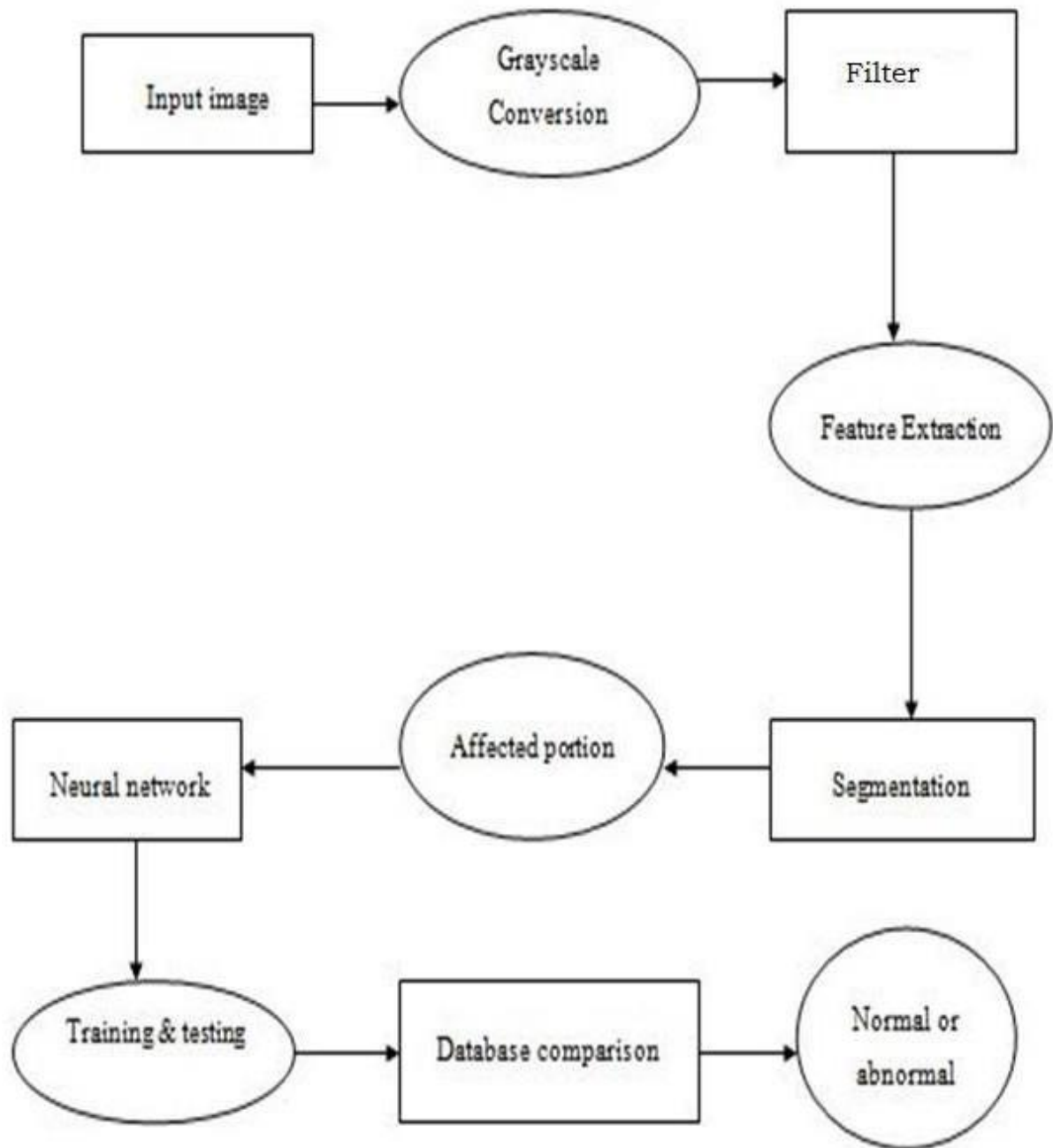


Fig 3.6 : ER Diagram

CHAPTER 4

RESULTS AND DISCUSSION

In this paper, we study a general inference framework for extracting liver tumors from medical image sequences. A collaborative formulation of tumor segmentation is discussed by jointly integrating region and boundary information. Here we used the Active contour segmentation algorithm is used in order to segment the portion of defected areas. We used to establish the back propagation neural network concept for training the image and testing the image with the help of weight estimating classifier. The result image will compared with the dataset images and it will display whether it is benign or malignant.

In the proposed system an enhanced interactive model is designed. An interactive sequence of images is fetched from the scanner database. Those images are pre processed and further segmented for the required feature. The segmented data is further classified through a motion based active contour segmentations in which the image sequence if validated frame by frame for the set of duration. Here the threshold required for segmenting adjusts itself according to the segmented area and position. The result image will compared with the dataset images and it will display whether it is benign or malignant.

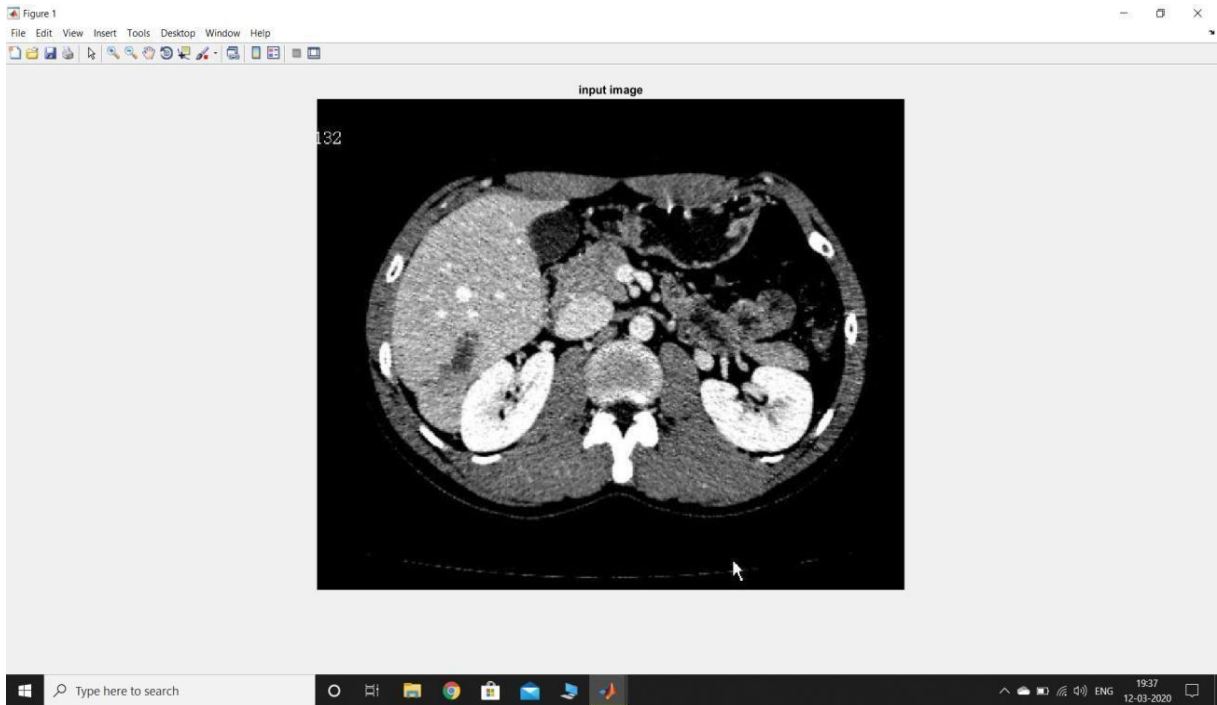


Fig. 4.1 : Input Image

Image Processing is a method to enhance raw images received from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-to-day life.

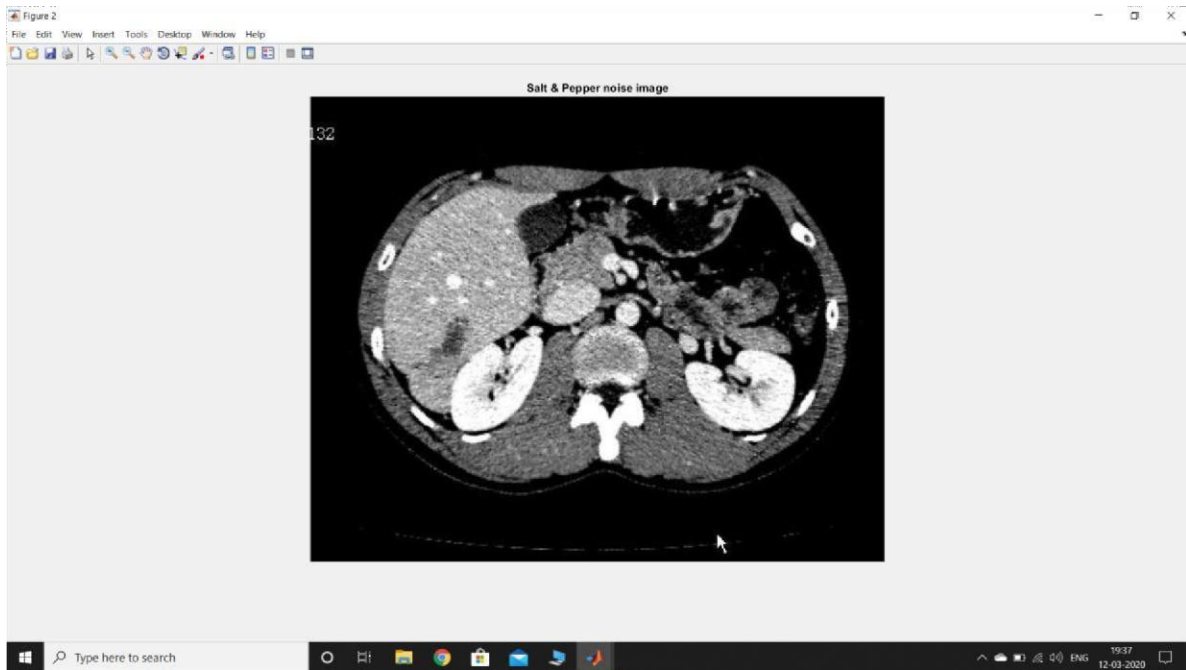


Fig. 4.2 : Salt And Pepper Noise Image

Salt and pepper noise is a form of noise sometimes seen on images. This can be caused by sharp and sudden disturbances in the image signal.

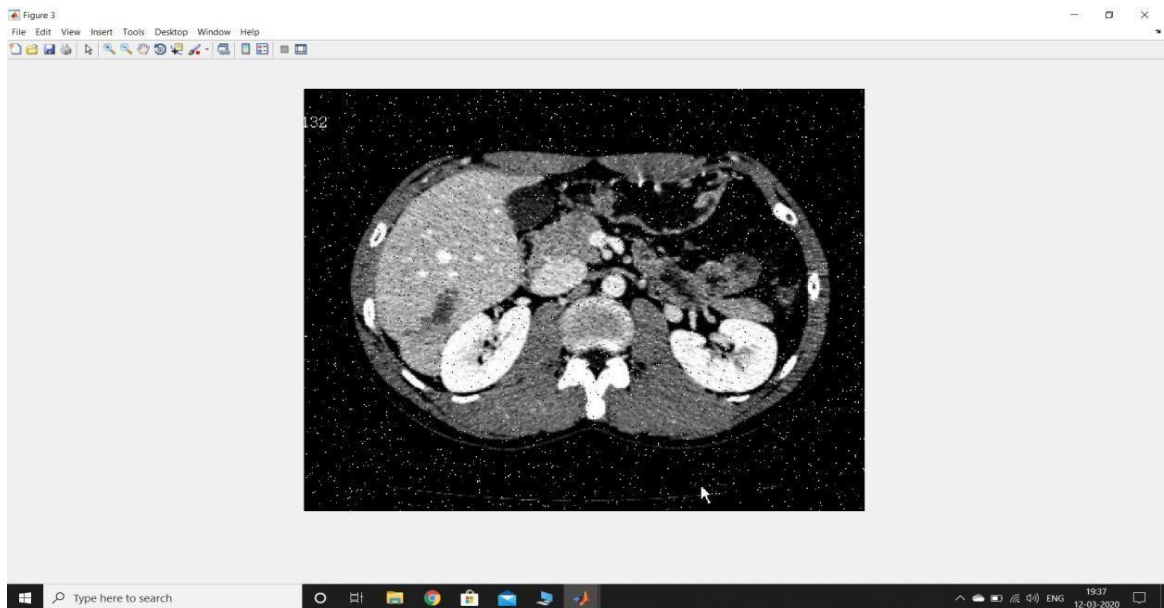


Fig. 4.3 : Grey Scale Image

A greyscale image is made up of pixels, each of which holds a single number corresponding to the gray level of the image at a particular location.

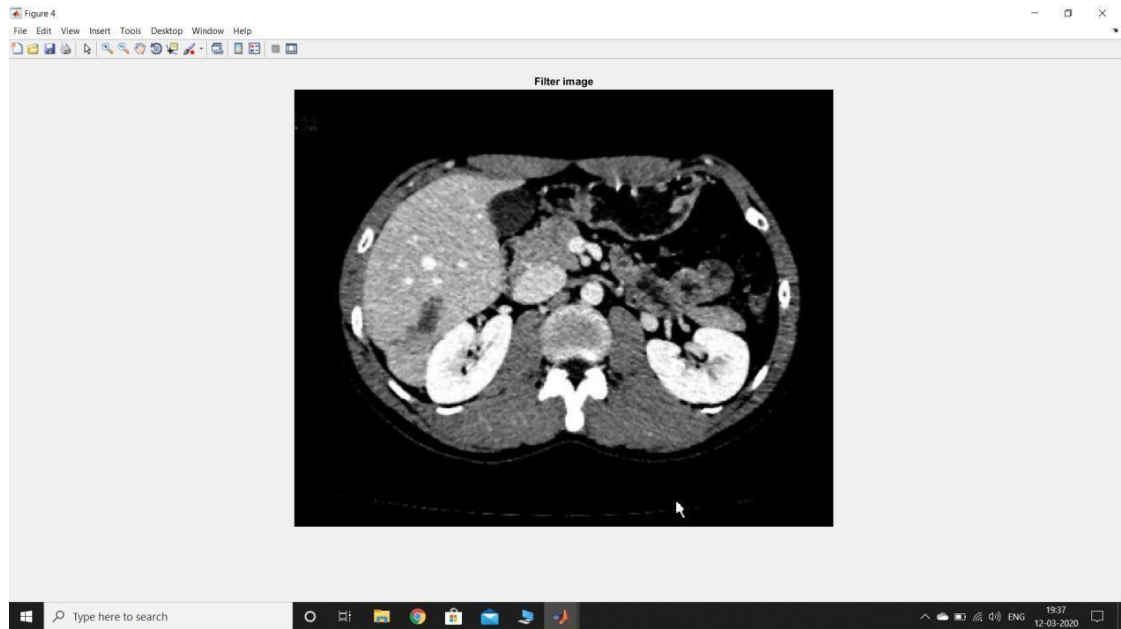


Fig. 4.4 : Filter Image

Filters are used to increase brightness and contrast as well as to add a wide variety of textures, tones and special effects to a picture.

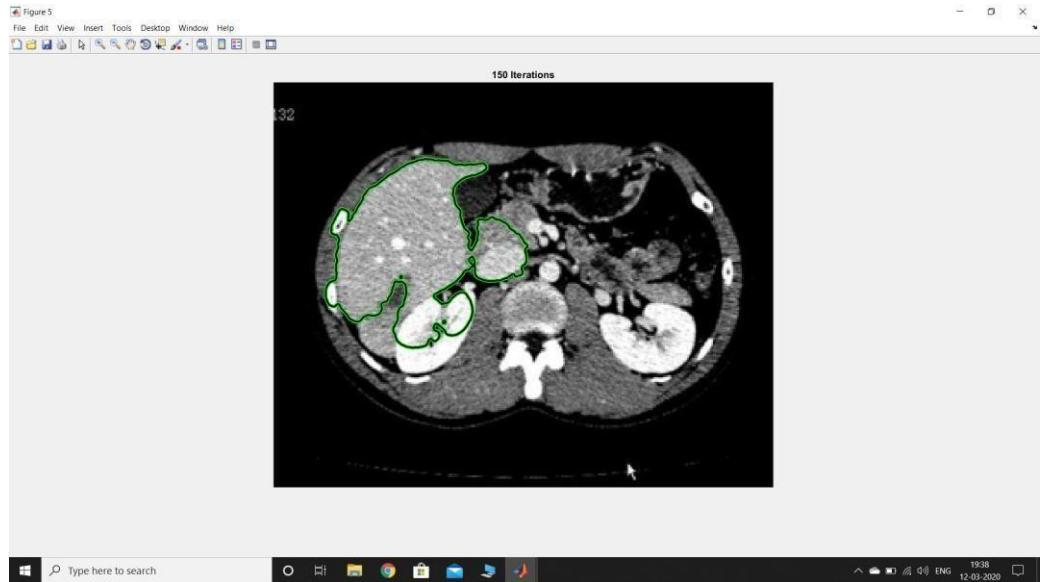


Fig. 4.5 : Image With 150 Iterations

Image resolution continued to improve well beyond the image that we get after the filtered image. After the first 150th iteration the following image is obtained.

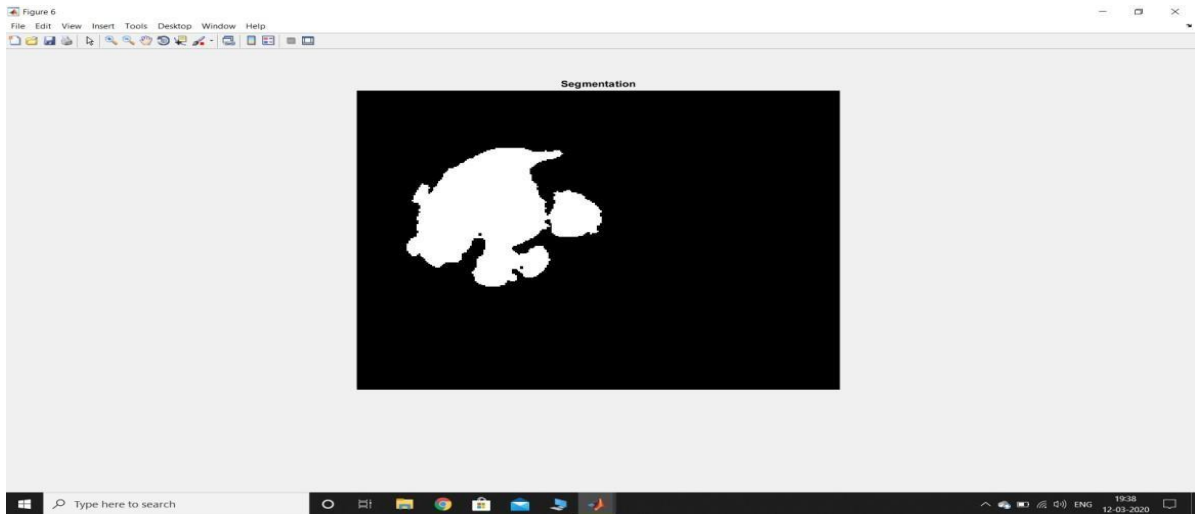


Fig. 4.6 : Segmented Portion

Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and or change the representation of an image into something that is more meaningful and easier to analyze.

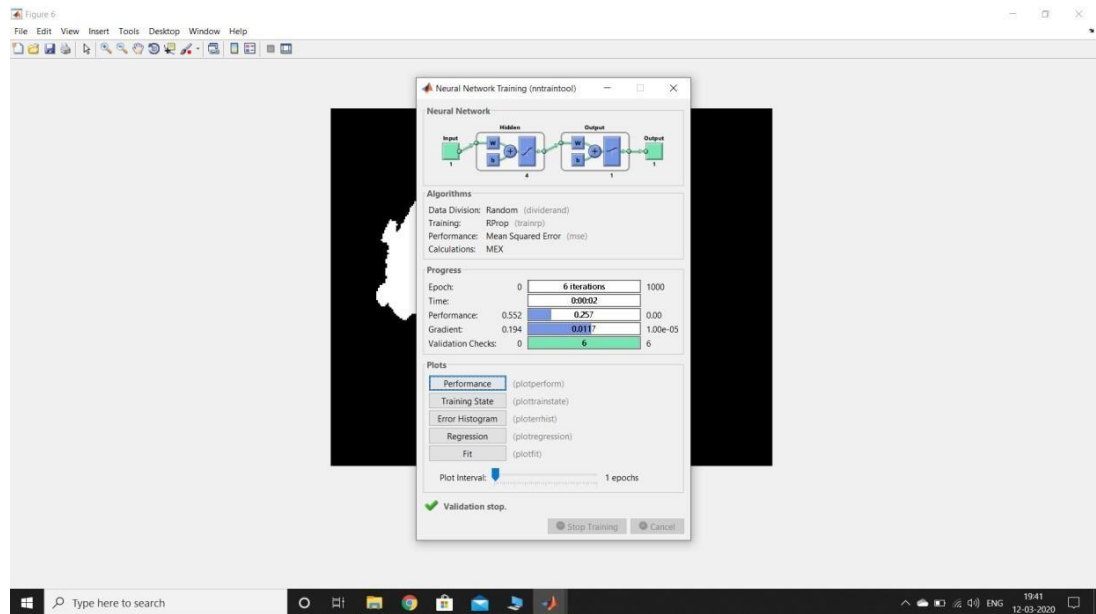


Fig. 4.7 : Neural Network Training

Fitting a neural network involves using a training dataset to update the model weights to create a good mapping of inputs to outputs. Training a neural network involves using an optimization algorithm to find a set of weights to best map inputs to outputs.

CHAPTER 5

SUMMARY AND CONCLUSION

5.1 CONCLUSION

An interactive sequence of images is fetched from the scanner database. Those images are pre processed and further segmented for the required feature. The segmented data is further classified through a motion based active contour segmentations in which the image sequence is validated frame by frame for the set of duration. Here the threshold required for segmenting adjusts itself according to the segmented area and position. The result image will be compared with the dataset images and it will display whether it is benign or malignant.

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APPENDIX

A. SOURCE CODE

```
%% MAIN FUNCTION
%% Preprocessing
[filenamefp, pathnamefp]=uigetfile({'*.jpg;*.jpeg;*.bmp;*.tif;*.png;*.gif','All Image
Files';...
    '*. *','All Files' },'mytitle',...
    'C:\Work\image');
fp=strcat(pathnamefp, '/', filenamefp);
%% read image
I1=imread(fp);
figure;imshow(I1);title('input image')
pause(2);
%% Grayscale image
I2=rgb2gray(I1); figure,imshow(I2); title('Grayscale image');
pause(2);
%% Noise image
J = imnoise(I2,'salt & pepper',0.02); figure,imshow(J);
title('Salt & Pepper noise image')
pause(2);
%% Filter image
I4=medfilt2(J); figure,imshow(I4);
title('Filter image'); pause(2);
%% segmentation
m = zeros(size(I4,1),size(I4,2));      m(111:222,123:234) = 1;
I = imresize(I1,.5);
m = imresize(m,.5);
% figure,imshow(I),title('Input Image');
% figure,imshow(m),title('Initialization');
```

```

figure,title('Segmentation');
seg = region_seg(l, m, 150);
figure,imshow(seg),title('Segmentation'); pause(2);
stats = regionprops(seg,'area');
area=stats.Area;
%% back propogation
hiddenLayerSize = 4;
net = patternnet(hiddenLayerSize);
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};
net.divideFcn = 'dividerand'; % Divide data randomly net.divideMode = 'sample'; %
Divide up every sample net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
net.trainFcn = 'traincgb'; % conjugate gradient backPropagation
net.performFcn = 'mse'; % Mean squared error
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
'plotregression', 'plotfit'};
inputs=[1 2 3 4];
targets=[0 1 1 0];
[net,tr] = trainrp(net,inputs,targets);
outputs = net(inputs);
ktry=net(targets); % Just trying gsubtract
errors = gsubtract(ktry,outputs); targets=ktry;
performance = perform(net,targets,outputs)
trainTargets = targets .* tr.trainMask{1}; valTargets = targets .* tr.valMask{1};
testTargets = targets .* tr.testMask{1}; trainPerformance =
perform(net,trainTargets,outputs); valPerformance = perform(net,valTargets,outputs);
testPerformance = perform(net,testTargets,outputs);

view(net)

```

```

if (area>5000&area<9000)    out='benign' elseif (area>9000)    out='malignant'
elseif(area<5000)
    out='non tumor'
end

```

```

msgbox(out)

```

```

%% IMAGE DISPLAY PRASE PV PAIR

```

```

function [common_args,specific_args] = imageDisplayParsePVPairs(varargin)

```

```

%imageDisplayParsePVPairs Pure input parser for image display functions.

```

```

% [common_args,specific_args] =

```

```

% imageDisplayParsePVPairs(specificNames,varargin) parse inputs for image
display % functions including properties specified in property value pairs. Client-
specific % arguments specified in specificNames are returned in specific_args.

```

```

%

```

```

% common_args is a structure containing arguments that are shared by imtool and
imshow.

```

```

%

```

```

% specific_args is a structure containing arguments that are specific to a %
particular client. Arguments specified in specific_args will be returned % as fields of
specific_args if they are given as p/v pairs by clients.

```

```

% Copyright 2008-2014 The MathWorks, Inc.

```

```

specific_arg_names = varargin{1}; varargin = varargin(2:end);

```

```

% Initialize common_args to default values. common_args = struct('Filename','...',

```

```

    'CData', [],...

```

```

    'CDataMapping','...',...

```

```

    'DisplayRange',[],...

```

```

    'Colormap',[],...

```

```

'Map',[],...
'XData',[],...
'YData',[],...
'InitialMagnification',[]);

specific_args = struct([]);

num_args = length(varargin);

params_to_parse = false;

% See if there are parameter-value pairs
% DISPLAY_FUNCTION(...,'Colormap', CMAP,...
%           'DisplayRange', RANGE,...
%           'InitialMagnification', INITIAL_MAG,... %           'XData', X, ... %
'YData', Y,...) string_indices = find(cellfun('isclass',varargin,'char')); valid_params =
{'Colormap','DisplayRange','InitialMagnification',...
 'XData','YData'};
valid_params = [valid_params,specific_arg_names];

if ~isempty(string_indices) && num_args > 1    params_to_parse = true;

is_first_string_first_arg = (string_indices(1)==1);

nargs_after_first_string = num_args - string_indices(1);
even_nargs_after_first_string = ~mod(nargs_after_first_string,2);

if is_first_string_first_arg && even_nargs_after_first_string    %
DISPLAY_FUNCTION(FILENAME,PARAM,VALUE,...)    param1_index =
string_indices(2);    else

```

```

        %   DISPLAY_FUNCTION(PARAM,VALUE,...)                                     %
DISPLAY_FUNCTION(...,PARAM,VALUE,...)
    param1_index = string_indices(1);

    % Make sure first string is a real parameter, if not

% Approximation accuracy2=(100-randi(7));
%% TRAINING
function [pk]=training(path) for i=1:20
    nam=num2str(i);   ext='.png'; filename=strcat(path,nam,ext);

    I=imread(filename); subplot(2,2,1);
    imshow(I);
    title('Train input'); lHSV=rgb2hsv(I); subplot(2,2,2); imshow(lHSV); title('HSV
    Converted'); lgray=rgb2gray(I); subplot(2,2,3); imshow(lgray); title('Gray Converted');
    % histogram(I);
    % title('Histogram of input Image');

    ledge = edge(lgray,'canny'); level=graythresh(lgray); lbin=im2bw(lHSV,0.6);
    subplot(2,2,4);
    imshow(lbin); title('Edge');

    cc = bwconncomp(lbin); pk(i)=((cc.NumObjects))
    pause(1);

end

```

B. PUBLICATION

Gorantla Ramya	Goparaju Prathima	Mrs. D. Usha Nandini
Computer Science and Engineering	Computer Science and Engineering	Computer Science and Engineering
Sathyabama Institute of Science and Technology Chennai, India	Sathyabama Institute of Science and Technology Chennai, India	Sathyabama Institute of Science and Technology Chennai, India
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INTERACTIVE MEDICAL IMAGE SEGMENTATION USING DEEP LEARNING WITH IMAGE-SPECIFIC FINE TUNING

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Abstract:- Deep learning with convolution neural networks (CNNs) has accomplished cutting edge execution for computerized therapeutic image segmentation. Nonetheless, programmed segmentation techniques have not shown adequately precise and vigorous outcomes for clinical use because of the inalienable difficulties of medicinal images, for example, poor image quality, distinctive imaging and segmentation conventions and varieties among patients. Intuitive segmentation regularly requires image explicit figuring out how to manage enormous setting varieties among various images however current CNNs are not versatile to various test images, as parameters of the model are found out from preparing images and afterward fixed in the testing stage without image explicit adjustment. The Proposed framework center around intuitive tumor segmentation of restorative image arrangements utilizing deep neural system. The proposed work uses design based grouping utilizing neural system work. Versatile Hirerical movement segmentation is planned in the proposed region.

I INTRODUCTION

Medicinal image segmentation, recognizing the pixels of organs or sores from foundation restorative images, for

example, CT or MRI images, is one of the most testing undertakings in therapeutic image examination that is to convey basic data about the shapes and volumes of these organs. Numerous scientists have proposed different robotized segmentation frameworks by applying accessible advancements. Prior frameworks were based on customary techniques, for example, edge location channels and numerical strategies. At that point, AI approaches removing hand-created highlights have turned into a prevailing system for a significant stretch. Planning and extricating these highlights has consistently been the essential worry for growing such a framework and the complexities of these methodologies have been considered as a critical confinement for them to be sent. During the 2000s, inferable from equipment improvement, deep learning approaches came into the image and began to exhibit their impressive abilities in image handling errands. The promising capacity of deep learning approaches has put them as an essential alternative for image segmentation, and specifically for therapeutic image segmentation. Particularly in the past hardly any years, image segmentation dependent on deep learning methods has gotten tremendous consideration and it features the need of having a complete audit of it. Apparently, there is no complete survey explicitly done on restorative image segmentation utilizing deep learning methods. There are a couple of late overview articles on therapeutic image segmentation, In [49], numerous different segments of therapeutic image investigation like characterization, location, and enrollment is additionally secured which makes it medicinal image examination audit not a particular restorative image segmentation study. Because of the huge canvassed zone right now, subtleties of systems, abilities, and inadequacies are absent.

The chief test of using CNNs for shrewd division is that present CNNs don't summarize well to in advance unnoticeable thing classes that are missing in the planning set. Accordingly, they require named instances article class be accessible in the planning set. For therapeutic pictures remarks are every now and again expensive to pick up as both ability and time are required to convey exact remarks. This limits the introduction of CNNs to segment objects for which remarks are not available in the arrangement compose. Second, instinctive division normally requires imagespecific making sense of how to oversee colossal setting assortments among different pictures, then exist CNNs are not flexible to different test, It has been demonstrated that picture unequivocal modification of a pre-arranged Gaussian Mixture Model (GMM) helps with improving division precision [6]. In any case, changing from direct GMMs to notable yet complex CNNs right now not yet been delineated. Third, snappy deriving and memory adequacy are mentioned for clever division. They can be commonly easily achieved for 2D pictures, yet become considerably progressively unsafe for 3D pictures. For example, DeepMedic [7] tackles 3D close by fixes to diminish memory essentials anyway realizes a moderate conclusion. HighRes3DNet [8] tackles 3D whole pictures with respectably brisk enlistment

yet needs a great deal of GPU memory, provoking high hardware essentials. To make a CNN-based natural division system gainful to use, enabling CNNs to respond quickly to customer associations and to work on a machine with limited GPU resources (e.g., a standard work region PC or a PC) is appealing. DeepIGeoS [5] merges CNNs with customer interchanges and has demonstrated extraordinary insight. In any case, it has a nonattendance of adaptability to disguised picture settings. This paper acquaints another structure with address these troubles for profound learning-based instinctive division. To summarize to previously covered things, we propose a ricocheting box-based division pipeline that thinks the frontal territory from a given region of interest, and plan a 2D and a 3D CNN with incredible minimization to avoid over-fitting. To make CNNs adaptable to different test pictures, we propose picture unequivocal adjusting. Besides, our frameworks consider an equality among open field, inferring time and memory profitability so as to be responsive to customer associations and have low essentials to the extent GPU resources.

II

RELATED WORK

Speculatively, it is shown that all the more profound frameworks have higher capacity to learn, yet progressively profound frameworks experience the evil impacts of edge vanishing issue just as face the even more issue that should be tended to of defilement [13]. It suggests with the significance extending, the exactness gets drenched and subsequently rapidly spoils. To misuse from all the more profound framework structure, He et al. [13] introduced the waiting frameworks which were from the start created for basic picture division on 2D pictures. At the present time, of consistently reinforcing the stacked layers with the component map, a waiting guide is supported to each couple of layers. So to speak, the rest of the maps are skip affiliations, allowing the framework to redirect the auxiliaries through the framework by avoiding a couple of layers.

For customary picture division, FCN [9] and DeepLab [10] are among the top tier performing systems. For 2D biomedical picture division, beneficial frameworks, for instance, U-Net [11], DCAN [12] and Nbla-net [13] have been proposed. For 3D volumes, fix based CNNs have been proposed for division of the cerebrum tumor [7] and pancreas [14], and even more prevailing through and through 3D CNNs consolidate V-Net [15], HighRes3DNet [8], and 3D profoundly oversaw framework [16]. A wide extent of instinctive division methods have been proposed [2]. Specialist methodologies join Graph Cuts [17], Random Walks [18] and GeoS [19]. Computer based intelligence has been conspicuously used to achieve high accuracy and cooperation capability. For example, GMMs are used by GrabCut [20] to divide concealing pictures. Online Random Forests (ORFs) are used by Slic-Seg

[21] for placenta division from fetal Magnetic Resonance pictures (MRI). In [20], dynamic learning is used to part 3D Computed Tomography (CT) pictures. They have achieved more exact divisions with less customer relationship than standard instinctive division methods.

To combine customer participations with CNNs, DeepCut [3] and ScribbleSup [2] propose to utilize customer gave

skipping boxes or scribbles, yet they use customer coordinated efforts as insufficient remarks for the planning set rather than as bearing for overseeing test pictures. 3D U-Net [14] gains from clarifications of specific cuts in a volume and produces a thick 3D division, anyway isn't responsive to customer affiliations. FCN is gotten together with customer participations for 2D RGB picture division, without alteration for remedial pictures. DeepIGeoS [5] uses geodesic division changes of scribbles as additional channels of CNNs for shrewd division, yet can't oversee effectively subtle thing classes. Past learning-based instinctive division strategies every now and again use picture express models.

For example, GrabCut [20] and Slic-Seg [21] gain from the target picture with GMMs and ORFs, exclusively, so they can be especially changed in accordance with the specific target picture. Taking in a model from an arrangement set with picture unequivocal change in the testing stage has in like manner been used to improve the division execution. For example, a flexible GMM has been used to address the dispersal dumbfound between the readiness and test pictures [6]. For CNNs, tweaking [15] is used for region sagacious model change in accordance with address the course fumble between different getting ready sets. In any case, the extent that we might know, this paper is the essential work to propose picture unequivocal model modification for CNNs.

III

EXISTING SYSTEM

Intuitive segmentation regularly requires image explicit figuring out how to manage huge setting varieties among various images though t CNNs are not versatile to various test images by way of parameters of the model are found out from preparing images and afterward fixed in the testing stage without image explicit adjustment. They proposed a jumping box based segmentation pipeline that concentrates the closer view from a given district of enthusiasm with great minimization to maintain a strategic distance from over-fitting.

IV

PROPOSED SYSTEM

In the Proposed framework center around intelligent tumor segmentation of medicinal image groupings utilizing deep neural system. The proposed work uses design based grouping utilizing neural system work. Versatile Hirerical movement segmentation is planned in the proposed zone. The term versatile implies that the limit required for portioning change itself as indicated by the sectioned region and position.

V

MODULE DESCRIPTION

5.1 PREPROCESSING :- This module comprises of Matlab executable directions helpful for separating the image outlines from the info database video. RGB board is utilized to see the red, green and blue segments of the image independently. It has just been referenced that a RGB image is cover of three two dimensional lattice. The discrete cosine change (DCT) is firmly identified with the discrete Fourier change.

5.2 SEGMENTATION :- The middle channel is utilized so as to expel the clamor from the consolidated RGB board. The image highlights like shading, weight, and profundity and pixel data to apply before the classifier (Deep neural system). Here we utilized the versatile various leveled movement segmentation calculation is utilized so as to fragment the segment of surrendered regions.

5.3 NEURAL NETWORK :- This module is utilized to set up the deep neural system idea for preparing the image and testing the image with the assistance of weight assessing classifier. the outcome image will contrasted and the dataset images and it will show whether it is ordinary or irregular. At last it shows what sort of the tumor.

VI CONCLUSION

Right now, first abridged the most famous system structures applied for medicinal image segmentation and featured their preferences over the progenitors. At that point, we gave an outline of the fundamental preparing procedures for medicinal image segmentation, their favorable circumstances, and downsides. At last, we concentrated on the primary moves identified with deep learning-based answer for restorative

image segmentation. Clever division much of the time requires picture express making sense of how to oversee gigantic setting assortments among different pictures yet current CNNs are not flexible to different test pictures, as parameters of the model are discovered from getting ready pictures and thereafter fixed in the testing stage without picture unequivocal change. The Proposed structure revolve around natural tumor division of therapeutic picture courses of action using profound neural framework. The proposed work utilizes configuration based portrayal using neural framework work. Flexible Hirerical development division is arranged in the proposed locale.

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