

CERVICAL CANCER PREDICTION USING MACHINE LEARNING

**Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering Degree in
Electronics and Communication Engineering**

By

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**DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
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SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade “A” by NAAC

JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119.

MARCH 2021



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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **T. SATHISH KUMAR (37130360)**, who carried out the project entitled “**CERVICAL CANCER PREDICTION USING MACHINE LEARNING**” under my supervision from NOVEMBER 2020 to MARCH 2021.

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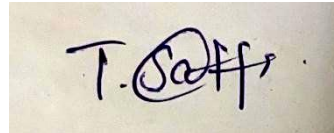
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DECLARATION

I, **T. SATHISH KUMAR (37130360)**, hereby declare that the Project Report entitled **CERVICAL CANCER PREDICTION USING MACHINE LEARNING** is done under the guidance of **Dr. S. EMALDA ROSLIN, M.E., Ph.D.**, is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Electronics and Communication Engineering**.

DATE:

A rectangular box containing a handwritten signature in black ink. The signature appears to be 'T. Sathish' with a stylized flourish at the end.

PLACE:

SIGNATURE OF THE CANDIDATE

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to Board of Management of **SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

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I consider my self-most fortunate and immensely privileged to have worked under the guidance of **Dr. S. EMALDA ROSLIN, M.E., Ph.D.**, Department of Electronics and Communication Engineering to complete this project successfully.

I express our heartfelt thanks to our family members and all our friends who helped me to complete our project successfully & finally, I thank the exciting Super Natural Power, the Almighty GOD.

ABSTRACT

Cervical cancer is one of the dangerous cancers acknowledged and is taking an important research domain in the image processing's field. It is a malignant disease that develops in the cells of the cervix or the neck of the uterus. The essential problem with this disease is that it cannot be detected at the early stages and it shows symptoms only at the final stages. To detect cancer in each stage you need unique functions and have three important stages: RGB2LAB color conversion, Entropy Measurement and classification. In this work, the GMM (Gaussian mixture model) is used to the pixel of an image as training data. Neural Network (NN) is a combination of associated supervised learning methods which is used for analyzing data and identifying patterns. It is also used for statistical classification as well as regression analysis. In a PNN (Probabilistic Neural Network), the methods of processes are arranged into a a number of layered feed forward network. Four-layer neural network of the sort proposed can record various input patterns to several number of classifications. Realizing the very factual diffusion of screening test has therefore been advanced in attempting to be administered as early cervical precancerous screening equipment. The proposed algorithm extracts features from the picture extra accurately.

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LIST OF ABBREVIATIONS

CT	-	Computed tomography
ECC	-	Endocervical Curettage
GLCM	-	gray-level co-occurrence matrix
GRNN	-	General Regression Neural Networks
LBP	-	Local binary patterns
LEEP	-	Loop electrosurgical excision procedure
LTP	-	Local ternary patterns
MRI	-	Magnetic resonance imaging
NN	-	Neural Network
PET	-	Positron emission tomography
RBF	-	radial basis function
UWB	-	ultra-wideband

CHAPTER 1

INTRODUCTION

The most common type of cancer is cervical cancer that has been occurring in human. High accuracy is needed for automatic categorization as well as tumor identification in various medical digital images because it is dealing with life of humans. The medical institutions require the help of computers in order to obtain better results in humans, where cases of false negative should be at an extremely low rate. For the best detection of tumors, the medical images' double reading is required. This could lead to a higher expense implied for this double reading. Hence usages of various assisting software are granted a great interest by the various medical institutions in the latest twenty first century. Conventional methods like diagnosing and monitoring the diseases depend upon the identification of certain characteristics by the specialist. Since many people are there in ICU and for the constant surveillance of this disease many automatic diagnostic techniques were developed in different parts of the world. The most qualitative diagnostic rules changes into a more intent based quantitative characteristic classification problem by the working of such methods.

The intensity of pixel and some bodily features are used for automatic classification of cervical magnetic resonance images. This method is used in this work. Reliable and automatic methods are currently used for tumor identification and they are of great need and interest. Currently there are no other methods for tumor identification. In the categorization MR image problems' data, the neural network is not completely used yet. It also includes classification and clustering methods which are particularly used for MR images involving large amount of data. If it is done manually it takes a great quantity of time and energy. As a result, a thorough understanding of classification, clustering or recognition techniques is critical for the development of NN (neural networks) systems, especially in the field of medication.

1.1 CONVENTIONAL MEDICAL DIAGNOSTIC TECHNIQUES

Doctors will use a variety of methods to identify and diagnose the cancer. The scanning is also do scans to observe whether if the cancer can spread from one area to the other area of the body from where it began. It's known as metastasis when this occurs. Imaging scans provide images of the insides of the body. Doctors may also conduct experiments to determine which therapies are most effective.

A biopsy is by far the surest method for a physician to determine whether a component of a body has cancer in several types of cancer. A small quantity of tissue taken by the doctor for laboratory examination from the patients affected part is called a biopsy. If a biopsy isn't an option, the doctor can recommend other tests to aid in the diagnosis.

The options for diagnosing cervical cancer are discussed in this section. Not all of the tests mentioned below will be used by each person. Any of more of those exams can also be useful in helping the doctor schedule your cancer treatment.

- The kind of cancer assumed
- Based on the patient's sign and symptom.
- Patient's age and common wellbeing.
- The outcome of previous medical tests.

Cervical cancer will also be diagnosed using the following tests:

Bimanual pelvic examination and sterile speculum examination

The patient's uterus, cervix, ovaries, vagina, and other nearby organs for any irregular adjustments will be examined by the specialist. To begin, the doctor will check whether if there is any modifications to the vulva in the outside of the body and look inside the vagina and see the cervix with the help of an apparatus called a speculum to remain the vaginal parapet intact. Also, at the same time a Pap examination is normally performed. The doctor will place two

fingers of one hand inside the vagina while softly pressing the opposite hand, since there is no visibility of the surrounding organs. This test only lasts a few minutes and is performed in a physician's workplace consultation room.

Pap test

The physician scrapes the cervix's surface during a Pap test, and inside collecting cell samples for examination. Doctors can also find cancerous cells more easily thanks to improved Pap test procedures. Since cells are often drying out, coated with blood or mucus, or gather collectively on the surface, traditional Pap tests can be difficult to read.

- Computer screening, also known as Auto Pap or Focal Point, involves scanning a sample for suspicious cells using a computer.

HPV typing test

On a panel of cervix cells, the operation is performed. HPV testing may be done concurrently with a Pap test or at the end of Pap test shows abnormal cervix shifts. HPV16 and HPV18 are high-risk HPV strains. They are mainly seen in patients of cervical cancer and can assist validating a analysis. If the physician has said that the HPV result was "positive," high-risk HPV is founded. HPV testing alone is inadequate for a cervical cancer diagnosis because lots of women bear HPV are not having the cervical cancer.

Colposcopy

A colposcopy may be used to look for abnormal areas on the cervix. A cervix biopsy may also be guided by a colposcopy. A colposcopy is performed using a special type of instrument known as a colposcope. The colposcope magnifies the cells of the following, the cervix and vaginal canal in a similar manner to a microscope. It allows the doctor to see the vaginal tissues, and thus the cervix, in a lighted, magnified view. The examination is close to that of a speculum since the colposcope isn't inserted into the body. It's washed out at the

doctor's office on a regular basis and has no negative side effects. It is also possible to perform it on pregnant women.

Biopsy

Other scans normally is able to indicate the presence of cancer, while only a biopsy can confirm the diagnosis. If the lesion is small, the doctor will be able to extract it completely during the biopsy.

Biopsies come in a diversity of various shapes and sizes. Most people are wiped out in the doctor's premises, with the help of a local anesthetic used to relieve the pain. During a biopsy, there could be any bleeding and other discharge. There may be a pain, similar to menstrual cramps.

Endocervical Curettage (ECC)

ECC would be seen if the doctor wishes to see a neighborhood beyond the cervix opening that can't be seen during a colposcopy. During this operation, doctors scrapes small volume of tissue from inner surface of opening of the cervix using a small spoon-shaped device called a curette.

Loop electrosurgical excision procedure (LEEP)

The hook is used to extract tissue for laboratory analysis. A LEEP is used to kill a precancer or a cancer in their premature stages of disease.

Conization (a cone biopsy)

Conization may also be used to cure a cancer or a pre-cancer in their early stages. It is performed with the help of a local anesthetic which should be completed in a doctor's clinical environment. If the biopsy reveals that the patient is having a cervical cancer, doctors normally will send to a gynecologic oncologist, a specialist in treating such kind of cancers. Additional scans to determine if the cancer has progressed past the cervix could be recommended by the specialist.

Pelvic examination under anesthesia

The specialist can go back to the pelvic region while the patient is given beneath anesthesia where in situations, it is appropriate for the treatment planning.

X-ray

An X-ray is a method of using radiation to produce a picture of the tissues within the body. Intravenous urography is one of the kind of x-ray used for examining the organs like kidneys and bladder.

Computed tomography (CAT or CT) scan

A Computer based Tomography scan uses multiple x-rays obtained from various angles to create images of contained in the body. A CT scan is often used to determine the tumors along with its size. Before the scan, using a special dye naming, contrast substance is often provided to provide more clarity on the image. This kind of dye is commonly pumped into the vein of the patient's or supplied to them in the form of a pill or fluid.

Magnetic resonance imaging (MRI)

The usage of Magnetic fields in the MRI provides accurate representations of the body when compared to the X-rays. MRI is sometimes used to determine the size of a tumor. Before the scan, a special pigment called a contrast material is provided to make the image clearer. This dye is commonly pumped into a patient's vein or supplied to them in the form of a pill or fluid.

Positron emission tomography (PET) scan

The PET or PET-CT scans are often paired with CT scans (see above), resulting in a PET-CT scan. And if it's a PET scan, the physician will inquire for this treatment. A PET scan is a method of creating images of organs and tissues inside the body. The material is then detected by a scanner, which provides photographs of the inside of the body.

Molecular testing of the tumor

The results of these assessments will assist you in deciding on your medical choices. Both tests can be recommended if there are indicating symptoms of bladder or rectal complications, and should be done at the same time as a pelvic examination.

Cystoscopy

A cystoscopy is a technique in which a doctor uses a small, lighted tube called a cystoscope to see interested areas related to the bladder and urethra. Since the tube is inserted into the urethra, the individual may be sedated. The cystoscopy is normally performed to find out whether the cancer has spread in to the bladder or not.

Sigmoidoscopy (Proctoscopy)

A sigmoidoscopy is a technique that aids a practitioner to examine the organs like colon and rectum with the help of sigmoidoscope, a light and thin , adjustable tube. Since the tube is inserted into the rectum, the individual will be sedated. To see how the disease has spread to the rectum, a sigmoidoscopy is used.

1.2 MOTIVATION

One of the most widespread gynecologic cancer specific in women in this universe is the cervical cancer. What's concerning is that 25 per cent of latest cervical cancer cases within the world and 27 per cent of deaths thanks to an equivalent are reported from India. Last year, as many as 1,22,844 new cervical cancer cases were reported within the country. Cervical cancer develops during a young population and 99.7 per cent of cases are related to Human Papilloma Virus - a virus infection caused through skin-to-skin contact.

However, in some instances, one will observe a watery, blood-stained discharge, intermittent vaginal bleeding following coitus and uncontrollable bleeding from the tumor bed.

The screening of cervical cancer is started at age 25 years in India, no matter sexual history. The varied screening tests conducted are HPV tests, Cytology by Pap test, co-testing with both HPV and cytology and VIA-visual inspection with ethanoic acid.

The Pap test has been shown to reduce cervical cancer prevalence by 79 percent and mortality by 70 percent.

The use of ethanoic acid to visually check the cervix may be an easy, accurate, and inexpensive outpatient screening examination that could be paired with simple treatment protocols for early cervical lesions. However, so as to stay the disease cornered, women must undergo screening tests frequently.

Women within the age bracket of 25 and 65 are advised to undergo a Pap test every three years or a co-testing every five years. Women above 65 years can discontinue screening if they documented three negative cytology results or two negative co-tests within the previous 15 years supported the cytology results, patients are advised about the frequency of tests they ought to undergo.

1.3 OBJECTIVES

- Early detection of cervical cancer thus allowing early intervention and treatment.
- Reduce the cervical cancer death and morbidity.
- Reduces financial burden of cervical cancer on long run.
- Promote women health by increasing awareness.
- Identify the risk factors of the diseases.

CHAPTER 2

LITERATURE REVIEW

2.1 LITERATURE SURVEY

Zhi Lu et. al (2012) used an optimization method in which performed the image segmentation of the cervical cells that are overlapped. From clumps of alternating cervical cells, the cytoplasm and nuclei are segmented. Due to the abundance of overlies between cells, the abnormality of the cell cytoplasm which is why the being there of the blood, mucus and the inflammatory cells, this problem is very popular. Our approach solves these problems by using a collaborative approach wherever each component represents the cell within the clump and consists of both unary (intracell) and two intelligent (intercell). These unary spheres are given by contour length, edge strength, and cell structure, while the intellectual limit is calculated by the planet of sparsely populated regions. Our approach allows us to examine the nuclei and cytoplasm from both floating and scattered cells in this way. We use a database with more than 900 images provided with naturally occurring images of free-flowing cervical cells, and the number of cells within a clump varies from 2 to 10, and the average interaction between two cells varies from 0.1 to 0.5 , providing scientific testing of our approach. This measurement test shows that our approach will effectively differentiate clumps of up to 10 cells when the interaction between two cells is minimal.

Karthigai Lakshmi and Krishnaveni (2014) explained how to separate various features of the cytoplasm and the nuclei from cervical cytology images using automatic methods. The Edge Sharpening filter improves the image's edges. The picture is then segmented into its various components likely as history, nucleus, and cytoplasm using a Gaussian mixture model of Expectation Maximization and the K-means clustering methods. Single and Multiple cervical

cytology cells have distinct characteristics. The nucleus to cytoplasm ratio is determined for multiple cell images. Commencing the cells with a single nucleus, a variety of features such as the central, border, mean intensity, area of nucleus and cytoplasm are derived. These characteristics may be used to assess the cancer stage.

Payel Rudra Paul et al. (2015) The most prevalent cancer in women is cervical cancer. The most successful procedure for identifying cervical precancerous cells is Pap smear screening. However, this technique takes a long time to finish and can even be incorrect. An artificial cervical cancer detection system is discussed in this article. This technique uses an adaptive median filter to eliminate impulse noise from Pap smear images before using a bi-group enhancer is done in order perform the distinguishing of nuclei pixels from other entity pixels. Separations of the nucleus regions from the cervical smear photographs are then being done using segmentation methodology. In the classification process, two clustering-based classifiers, K-nearest neighbour classifiers and minimum distance are used for the results verification. 158 Pap smear photographs from the DTU/HERLEV Pap smear benchmark database were used to test the methodology. The detection method's accuracy is 92.37 percent for minimum distance classifiers and 98.31 percent for K-nearest neighbour classifiers, respectively.

Cervical Cell Images Segmentation

Specific cell division is an important step in computer-assisted screening for early detection of cervical cancer. Due to the problems of abnormal contamination, low cell division and differentiation, a two-phase cell division method is recommended in Pap smear test images in their proposed studies. The first footstep is image classification using a hierarchical segmentation algorithm that looks at the following details such as spectral, shape, and gradient. The second phase attempts to distinguish the fragments obtained from the first phase in order to obtain the cytoplasm zones and nucleus regions. Experiments with two data sets demonstrate that this approach works well for the images with a an unique cell as well as images with a lot of overlapping cells.

S Pradeep Kumar Kenny et al. (2014) used the outlier detection and various removal methods for detecting the cancer lesions by using the prominent textural features. Cervical cyto photographs have sparked a lot of curiosity among scientists in the last few years. This is due not only to its lethal prestige, but also to the wide range of daunting unanswered problems it contains. Cervical cancer, like all other cancers, progresses through many stages before causing damage. A pathologist can diagnose these phases using sensory details such as shape, texture, and so on. However, since there aren't enough pathologists to go around, an automated device to identify these features is the only option. However since each image has different properties, finding a profound set of features which can be used to detect cancer for a particular stage of cancer is still a problem. In an automated system detecting the stage of cancer using a feature for a particular stage of cancer is not going to work. A combination of features can work but finding the right combination is a challenge. Too many features in the combination will drastically slow the system and too little will affect the accuracy of the system. To strike a balance between the two a unique technique using outlier detection and removal is used to isolate the best feature that can be used to detect a particular stage of cancer.

2.2 SUMMARY OF EXISTING WORK

The various classification techniques used in the literature are K-means clustering, Gabor Wavelet, and Normal threshold and SVM classifier. The key disadvantages of current work are that it is difficult to obtain reliable data that it is not applicable for many images for cancer diagnosis in a limited period of time, and that due to operator efficiency, the Medical Resonance images produce. Noise which can result in rigorous classification inaccuracies.

CHAPTER 3

PROPOSED METHODOLOGY

3.1 BLOCK DIAGRAM OF PROPOSED WORK

In the past, NNs have been used to solve classification problems. The NN classifier had high accuracy, a short training period, was resistant to weight adjustments, and needed no retraining. Starting with the data input and ending with the output, the proposed model has six steps. The image processing device must be the first footstep. For an image processing system, the processes that must be completed are image extraction and image enhancement. The above two steps are skipped in this article, and all photographs are gathered from publicly accessible sources. The proposed model necessitates the conversion of the image into a computer-readable format. MATLAB is used to transform the MR images into matrices. The NN is then used to categorize the MR images. Finally, at the conclusion of the implementation process, quality dependent on the results would be evaluated.

The input has been given the MRI image. The input image was converted to a mat format, and the weight was calculated as well. In order to use the PCA algorithm. The relationship between two or more variables is determined using a technique called as Principal Component Analysis (PCA) whose aim is to condense the data's high dimensionality values. Calculate the weight as well. After that, for classification purposes, construct a two-layer network called a NN (Neural Network). The neural network is a successful approach for tumors classification because it provides quick and reliable results. The neural network is a promising method for tumor classification because it provides quick and reliable results.

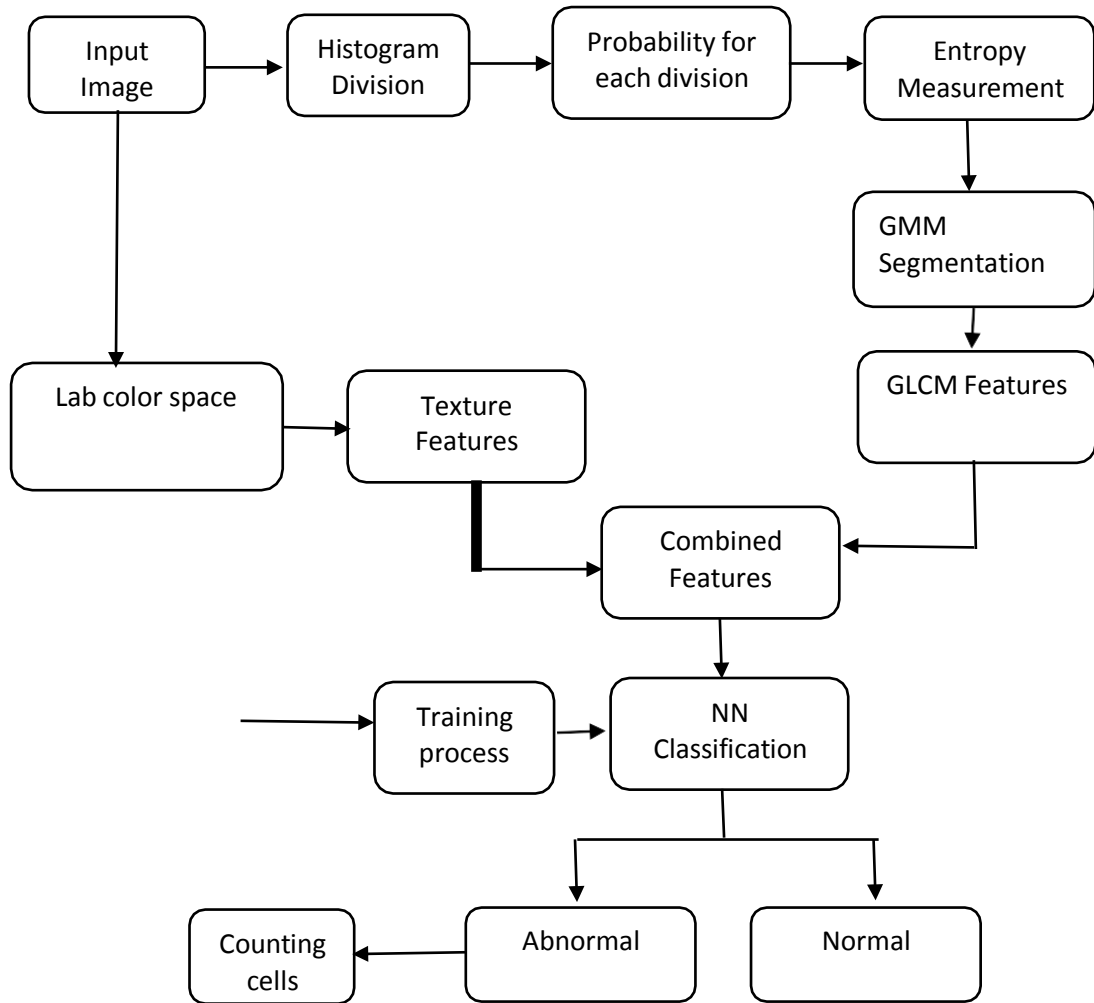


Fig. 3.1 Block diagram of proposed work

Neural networks are statistical structures that are loosely dependent on biological neuron behavior. A hundred neurons make up a standard artificial neural network. The human nervous system, on the other hand, is thought to be about 3×10^{10} neurons.

The first Perceptron model developed in 1958 has three layers: (1) a retina which transmit the inputs to the next layer from the first layer, (2) The associated units combining the inputs with weights and that triggered a threshold phase feature which is then fed into output layer, and (3) The Output layer which is combining the value. The employment of phase function in the neurons, however, made training expectations challenging. Marvin Minsky and Seymore Paper published a critical analysis of Perceptron in 1969, which revealed a number of critical flaws, and interest in Perceptron waned for a time.

David Rumelhart et al. published “Learning Internal Representations by Error Propagation” in 1986 and reignited interest in neural networks where a suggestion was made by them that a multilayer neural network having a nonlinear but differentiable changeover functions with the aim of avoiding the drawbacks of the phase functions used in the original Perceptron. They also presented a fairly powerful neural network training algorithm.

Cervical cancer is one of the a large amount common causes of fatality for women worldwide due to cancer. The best way to reduce mortality is to get and get tissue at an early age. The most widely used method of taking cervical cancer screening is X-ray mammography. However, it has major drawbacks. It has a high level of falsehood and false positives, for example, which could increase to 34%. As a result, medical science has prioritized the development of imaginative techniques that add, add, or change X-ray mammography. Several ways to think of a microwave have recently been developed. Many research teams around the world are currently investigating microwave ultra-wideband (UWB) imaging as a promising method. This method uses UWB lightweight horns to transfer UWB signals to cervical tissue and record scattered signals from various locations around the cervix. The difference in electrical activity between healthy tissue and tissue is the basis of this system. Various research groups around the world have found that strong cervical tissues have a dielectric from 5 to 9 and a conductivity ranging from 0.02 Sim to 0.2 S / m. Bad tissues having a fixed dielectric of about value 60 and with a conductivity of 2 Sim. Because of this, it is clear that the electrical potential of stable and malignant tissues is very different. From the point of view of the neural network, the diversity of risk factors for healthy and healthy tissue suggests that scattered signals are captured in various areas around the cervix with the signature of existing tumors. When signals found in different locations are compared, the location of the plant can be determined.

According to a review of the literature, most studies using neural networks in cervical cancer screening are aimed at assisting a radiologist in making accurate cervical cancer diagnoses on X-ray mammograms. [15] has used many neural network models as an example in the automatic acquisition of integrated computations for small counts in mammograms.

The neural network is widely used in UWB programs for detection of the arrival way of ultra wideband signals. It can be used to identify and locate 2.2 mm tissue around the same axis (single size) and double width by moving the signal receiver position 1 degree around the cervix. It shows how a neural network can be used to identify and find tumors in the cervical region with sizes as small as 1 mm in radius with the help of 4 permanent probes placed around the neck. For the purposes of this study, a three-dimensional cervical model was developed. Four antennas orbiting the cervical are bombarded with a pulsed plane electromagnetic wave, and the scattered signals are captured. The emitted pulse has a frequency spectrum of 3.1 to 10.6 GHz in the UWB band. The tumor is then detected and located by means of a basic feed-forward BPN network.

3.2 CERVICAL CANCER DETECTION USING MACHINE LEARNING

A. *Cervical Model*

There are four structures in the female cervical: fibro glands, the milk ducts, the connective tissue and the fat. These glands are organized into lobes, which are simply attached to the nipple by means of milk ducts. Fibrous threads connect cervical tissues to the skin. Researchers have used a variety of styles to depict cervical cancer. Two different measurements were considered for the model to emulate the normal condition with a full variety of sizes for the human cervical, as observed in Tables 3.1 and 3.2.

Table 3.3 shows the electrical properties of the various cervical tissues which was used in this study. The scale of the tumor radius which is used by researchers usually ranges approximately from 2 to approx 15 mm.

B. *Data*

The four probes were evenly spaced along the x-y axis, or cross-section plane, to produce the results. Cervical tumors can appear in almost every area of the cervical spine, but they are located in various parts of the spine. The full wave electromagnetic simulator CST microwave Studio is used for studying the entire cervical model, which includes the four probes used to gather dispersed signals.

For each probe, the processed data that reflects the dispersed signals is segmented into 500 samples. In those results, the tumor's signature is secret.

3.3 THE USED NEURAL NETWORK

The most excellent method for recognizing and discriminating between various sets of signals is the neural network. It is significant to decide an appropriate design and the learning algorithm while using a neural network to achieve the best performance. Unfortunately, there is no sure way to do so. The easiest way to do this is to pick what we think would fit based on history and then extend or shrink the neural network dimension in order to get a fair performance. Using MATLAB, we experimented with various sizes for neural network and discovered that one shown in Fig. 2 is the strongest in our case. It has a 2000-input input layer, a first hidden layer with eleven nodes and the TANSIG transfer function, a second hidden layer with seven nodes and the TANSIG transfer function and the output layer with PURELIN transfer function having only 2 outputs. One from the two of the outputs is used to detect tumors, while the other is used to pinpoint their location. The TANSIG transfer feature is used to restrict the signal to a range of -1 to 1. The PURELIN transfer feature is used in the output layer to include all potential tumor locations.

In two instances, the suggested the usage of neural network used to become aware of and find the tumor. The first part involved detecting and locating a tumor in a 2D model field. The tumor was placed at the core and randomly in the each of the four quadratures. The next stage involved detecting and locating tumors in a 3D model. Using the training algorithm, the neural network was trained with 100 sets of inputs (TRAINSCG). A total of 40 sets of inputs were used to measure each neural network's output.

Types of Neural Networks

- 1) A neural network that is artificial
- 2) Neural Networks with Probabilistic Properties
- 3) Neural Networks for General Regression

The most often used forms of neural networks are implemented by DTREG:

- a) The Multilayer Perceptron Networks (multilayer feed-forward networks)
- b) The Probabilistic Neural Networks (PNN)
- c) The Cascade Correlation Neural Networks and finally the
- d) The General Regression Neural Networks (GRNN).

are some of the kinds of neural networks

Radial Basis Function Networks

The various types of RBF networks are depicted below. They are

- a) Kohonen networks
- b) Functional Link Networks,
- c) Hebb networks
- d) Hybrid Networks
- e) Adaline networks,
- f) Gram-Charlier networks

3.4 THE MULTILAYER PERCEPTRON NEURAL NETWORK MODEL

The below Fig 3.2 depicts a Perceptron network having three layers.

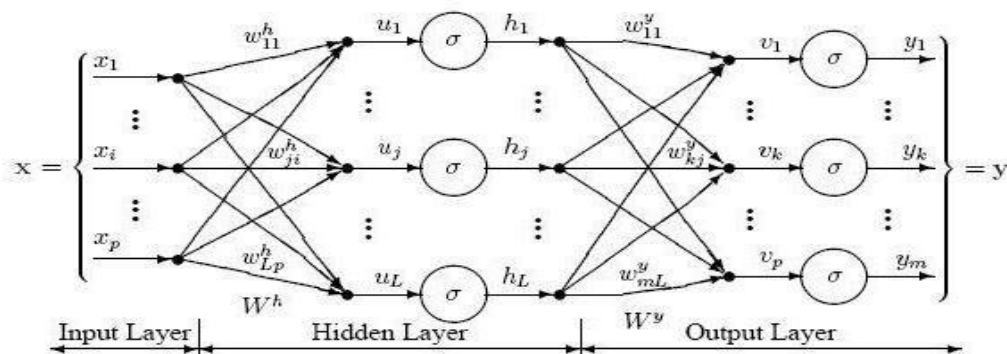


Fig. 3.2 The Model of Multilayer Perceptron Neural Network

This network consists of 3 neurons in the input layer in the left, 3 neurons in hidden layer (center), with 3 neurons in the right ie the output layer. Each predictive variant has its own neuron in the input layer. When working with phase flexibility, the $n-1$ neurons present are used in the representation of different n groups.

Input Layer

The input layer is given with a predictive value vector ($x_1 \dots x_p$). This input layer (or processing that precedes it) sets these values as the choice of each variant is -1 to 1. The standards are distributed to each particle in a layer hidden by the input layer. A permanent input of 1.0, known a bias, is provided for each layer that is hidden in addition to the predictive variables; prejudice is multiplied by weight and is applied to a number targeting the neuron.

Hidden Layer

The value from every key in neurons reaches the hidden layer neuron, it is combined with the weight (w_{ji}), where the weighted values were further added together to produce the combination value u_j . The amount of weight (u_j) is then transmitted by the use of transfer function, returning h_j . Extraction layer gets results from a hidden layer.

Output Layer

As the importance from each of the hidden layer reaches the neuron in the output layer, it is done by multiplication of the weight (w_{kj}), and the weighted values were added together to produce a mutual value v_j . This weighted value (v_j) is transmitted by the transfer function, which produces the assessment of y_k . Network results are represented by y values. When continuous targeted flexibility is used in retrospective analysis, the output layer consists of a single neuron that produces a single value y . In the segments of the phase-specific variables, the output layer consists of n different neurons that produce n values, one for each different n available group.

CHAPTER 4

NEURAL NETWORK ARCHITECTURE OF CERVICAL CANCER

While the formation of neural networks (NN) and normal neural regression networks (GRNN) are similar, there is a big difference: networks that make a distinction where the target neural variable is classified, and the normal neural regression networks make a retrospective as the target transformation continues.

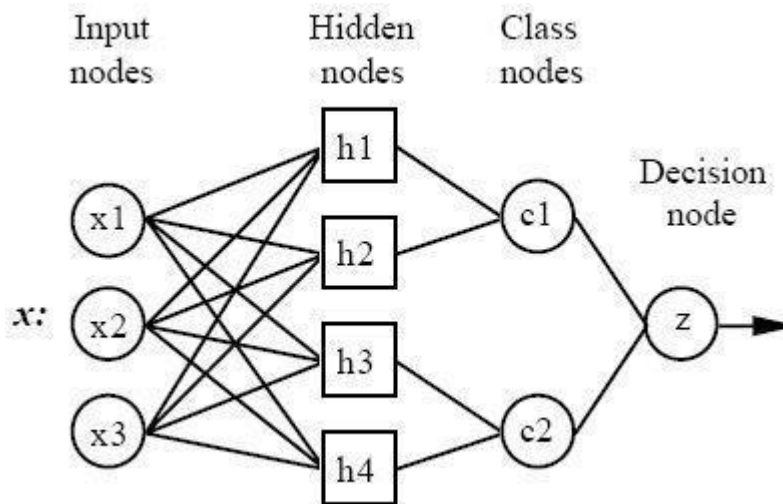


Fig.4.1 The Architecture of a NN

Usually all the Neural networks will have the four layers as mentioned below.

Input layer- Each predictive variable has its own neuron in the input layer. $n-1$ neurons is used for the spatial flexibility, where n is the number of phases. With intermediate output and interquartile scale distribution, input neurons (or pre-processing input phase) make the value range measured. Values are then assigned to each encryption neurons each of the input neurons.

The hidden layer – This Hidden Layer contains 1 neuron for the case of each training data collection. Along with target value set, the neuron maintains the values of the state's predictable variables. When given the x number of vector of the input values from input layer, the encrypted neuron calculates the Euclidean range of this test case from the center of the neuron along with uses RBF kernel function with sigma values (s). The resulted values are sent to neurons of the pattern layer.

The Summation layer / Pattern layer - The following network layer differs between NN and GRNN networks. In NN networks, a single pattern neuron is assigned to each phase of target variability. Each hidden neuron maintains a specific identification phase for each training case; the estimated amount released by the hidden neuron is fed to the neuron only of this pattern corresponding to the hidden neuron phase. This pattern neurons comprise values of the category which is represented.

In a GRNN network based sequence network, there are only 2 neurons. One neuron acts as a denominator summary unit, and the other acts as a numerator summary unit. Weight values from each hidden neuron were added together by the summary unit of the organization. For each secret neuron, a numerical summary unit uses weight values combined with the actual target value.

Decision Layer - In NN and GRNN networks, the judgment layer is different. In NN networks, the decision-maker compares the weighted votes accumulated on the pattern layer for each of the target category and utilizes the principal vote in the prediction of the target category.

4.1 GRNN NETWORKS

The aggregated value of a numerical summary unit is divided by the accumulated value in a system summary, and the result is used as the target value measured by the decision shell.

The diagram below depicts the real or proposed network used in our project.

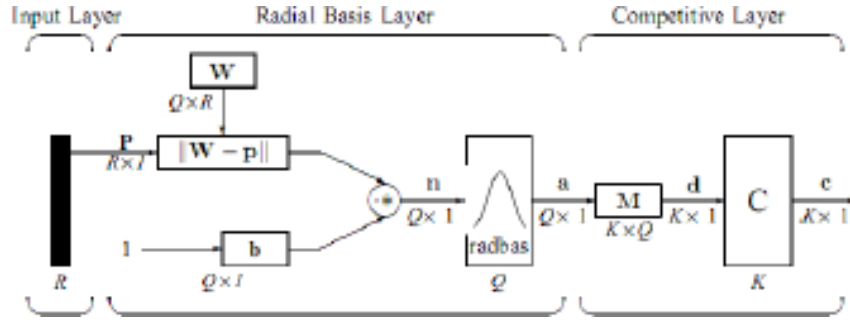


Fig. 4.2 GRNN Network

Input Layer

The black vertical bar represents the vector called as input vector, when denoted as p . It has the dimension R . $R = 3$ in this article.

4.2 THE RADIAL BASIS LAYER

Vector distance between the vector input and the weight vector formed by each line of the weight matrix W is determined in the Radial Basis Layer. The vector range is represented here as a dot product of two vectors [8]. Assume that W has a QR size. The dotted product of p and the i -th W -line reflects the i -part of the vector range $\|W - p\|$, its size is $Q * 1$. The minus sign, “-,” denotes the distance between vectors. The vector b of discrimination and then multiplied by the object and the element of $\|W - p\|$. The result is indicated by $n = \|W - p\| \cdot p$. In NN, the transformation function is included in the distance measure in relation to the institution. Described in this paper as $\text{radbas}(n) = 2n$ in (1) Each element of n is added to Eq. 1 to produce a compatible object for, Radial Basis Layer output vector.

Other features of Radial Basis Layer

If the input p equals the input line of the input weight W , the i -th section of equals 1. A radial base neuron with a weight vector similar to the input p vector produces a value close to 1, and the output instruments of the competition layer they transfer their values to competitive work. When the key in pattern

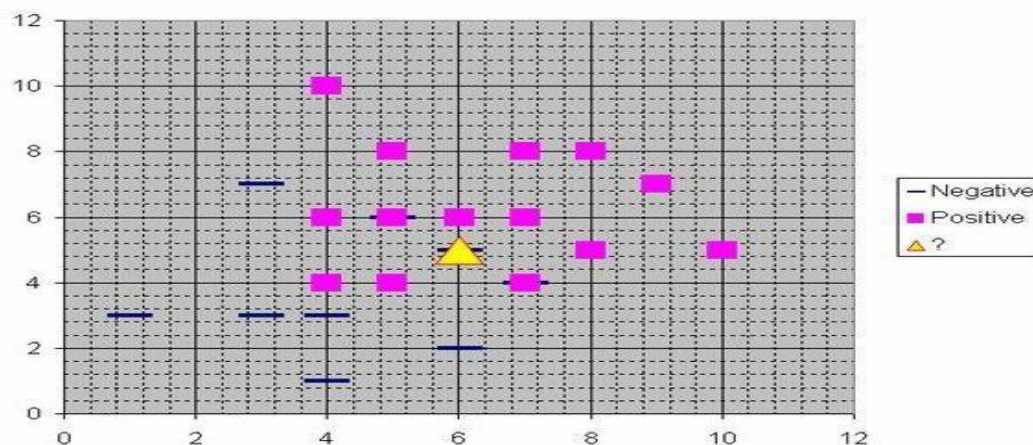
corresponds to many different training patterns, it is usually possible for several an element to be close to 1.

Competitive Layer

The Competition Layer is impartial. The vector a_n is initially multiplied by the weight matrix of layer M in the Competitive Layer, denoting the output of vector d. Competitive work, shown as C in Figure 2, returns 1 of the largest item d and 0 in all other items. The vector to produce a competitive job is defined as c. The number of tumors the device I can see is represented by 1 index c. In this article, the size of the output vector, K, is set to 5.

How NN network work

Although the implementation varies widely, these neural networks is almost identical to the K-Nearest Neighbor (k-NN) models. It aims the expected target value of any piece may being almost identical to other items with values that are close to predictive variables. Consider the following statistics:



Assume that each training set state has the variables, x and y respectively. As shown in the diagram, the cases are arranged by means of their links x , y . Assume goal flexibility has two categories: positive (square) and negative (dash shown).

Note how the triangle is correctly placed above the dash indicating the negative value. However, the dash is in an unusual location unlike other dashes,

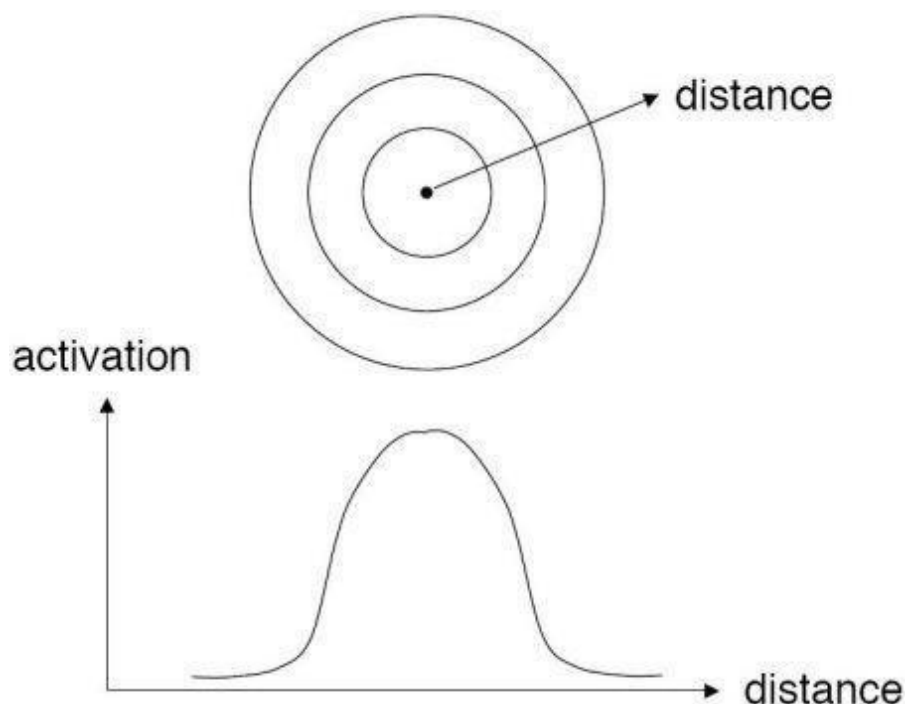
grouped at the bottom of the squares and on the left in the middle. As a result, the negative value that emerges can be overwhelming.

The closest neighbor selection used in this example is determined by the number of neighboring points under the consideration. If 1-NN is used with the nearest point only under consideration, the new point may simply be considered negative. If, on the supplementary way, a 9-NN split is utilised and only nine points are too close, influence of the 8-point points can exceed the nearest negative point.

The neural network expands for this reason by considering all the additional points. The distance between the estimated point and each of the points is calculated, and the weight (effect) of each point is calculated using the basic scattering function (RBF) used in the range. The function of the radial base derives its name from the radius range, which is a matter of function.

$$\text{Weight} = \text{RBF}(\text{distance})$$

The greater the distance between any other point and the novel point, the a smaller amount impact it is having.



4.3 THE RADIAL BASIS FUNCTION

Though there are many kinds of radial basis functions in usage, the most general is the Gaussian function:

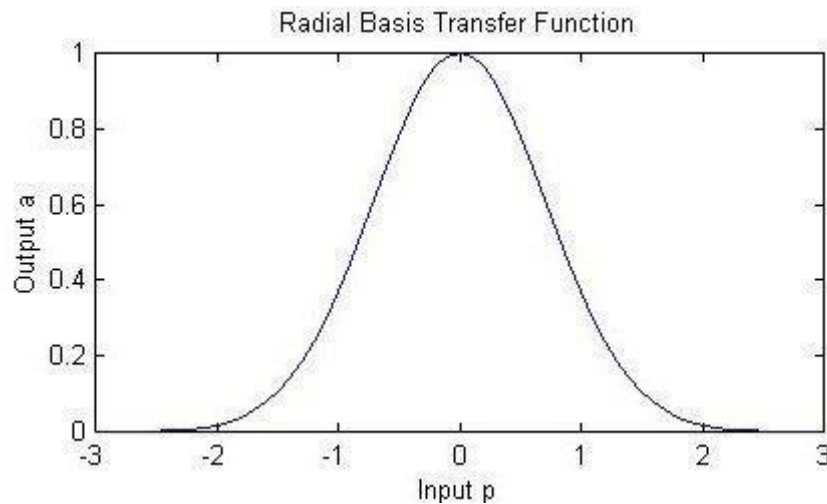


Fig. 4.3 Radial Basis Function

Advantages and disadvantages of NN networks

- 1) A NN/GRNN network is usually much easier to learn compared to a multilayer perceptron network.
- 2) NN/GRNN networks outperform multilayer perceptron networks in terms of accuracy.
- 3) NN/GRNN networks are largely unaffected by outliers (wild points).
- 4) NN networks provide precise expected goal likelihood ratings.
- 5) NN networks are getting around to Bayes optimum classification.
- 6) When it comes to classifying new instances, NN/GRNN networks are slower than multilayer Perceptron networks.
- 7) In order to store the model, NN/GRNN networks need more memory space.

Removing unnecessary neurons

One downside of NN models over multilayer Perceptron networks is their size, which is due to the fact that every training row has only one neuron.

DTREG has an alternative that causes it to delete unwanted neurons from the model after it has been developed.

The removal has three benefits

1. The size of stored model's is minimized.
2. The amount of time that is required for applying the model during scoring is minimized.
3. Removal of the neurons frequently rises the model's accuracy.

It is an iterative procedure to remove redundant neurons. The error of the model is measured using leave-one-out validation, which removes one neuron at a time. The neuron that produces the least error increase is then excluded from this model. The procedure is then replicated with the residual of the neurons until stopping condition is met.

As excess neurons are deleted, the study report's "Model Size" section reveals how the error varies with the number of neurons. By pressing Chart/Model scale, you can see a graphical representation of this.

There are three conditions that can be used to direct neuron removal:

1. Minimize error – If this alternative is chosen, the DTREG will delete neurons given that the leave-one-out error stays stable or decreases. It comes to a halt when it encounters a neuron whose exclusion will allow the error to exceed the minimum detected.
2. Minimize neurons – If this alternative is selected, DTREG excludes neurons before the leave-one-out error exceeding the error for the neuron-free model.

3. No of neurons – If this choice when used, DTREG eliminates the smallest amount important neurons so only the specified quantity of neurons remain.

New neural network

NEW NN forms a two-layered network. The first layer contains RADBAS neurons and uses DIST to measure its input intensity and NETPROD to calculate its network data. The second layer contains COMPET neurons and combines weighted input using DOTPROD and network input using NETSUM. Discrimination exists only in the first layer. NEWNN sets the initial layer weights in P 'and the first layer is targeted at 0.8326 / SPREAD, resulting in radial core functions exceeding 0.5 input inputs having +/- SPREAD. The weights of the second sheet, W2, are set to be T.

4.4 GAUSSIAN MIXTURE MODEL

An image is a matrix with each unit representing a pixel. The pixel value is a number that represents the image's intensity or color. Assume X is a random variable with these values. For the purpose of determining a probability model, we may assume a Gaussian distribution mixture of the following form:

$$f(x) = \sum_{i=1}^k p_i N(x | \mu_i, \sigma_i^2)$$

Where k represents the number of components or regions and

$$N(\mu_i, \sigma_i^2) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp\left(-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right)$$

Where μ_i and σ_i represent the mean and standard deviation of class i. The lattice data for a given image X are the pixel values, and MoG is our pixel-based model. However, the parameters are $\theta = (\mu_1, \sigma_1, \mu_2, \sigma_2, \dots, \mu_k, \sigma_k)$ and the number of regions in MoG can be estimated using a histogram of lattice results.

Local ternary pattern

Local ternary patterns (LTP) are a subset of Local binary patterns (LBP). Unlike LBP, it divides pixels into three values using a threshold constant. Using k as the constant value of threshold, c as the centre pixel value and p the value of a neighboring pixel, the result of threshold is:

$$\begin{cases} 1, & \text{if } p > c + k \\ 0, & \text{if } p > c - k \text{ and } p < c + k \\ -1 & \text{if } p < c - k \end{cases}$$

As a result, each threshold pixel has one of 3 values. After thresholding, the neighborhood pixels are merged to form a new ternary prototype. Since computation of a histogram of the ternary values yields wide variety, the ternary pattern is divided into 2 binary patterns.

This paper proposes a novel approach for feature extraction based on Local Ternary Pattern (LTP) and signed bit multiplication, with feature computation performed on the central pixel. The extracted features comprise the majority of the initial collection of learning images (training set). Once the characteristics of the test images have been removed, the image is labeled using an ANN classifier by comparing its feature vector to other train vectors in the database.

4.5 SPLITTING LTP INTO TWO LBP CHANNELS

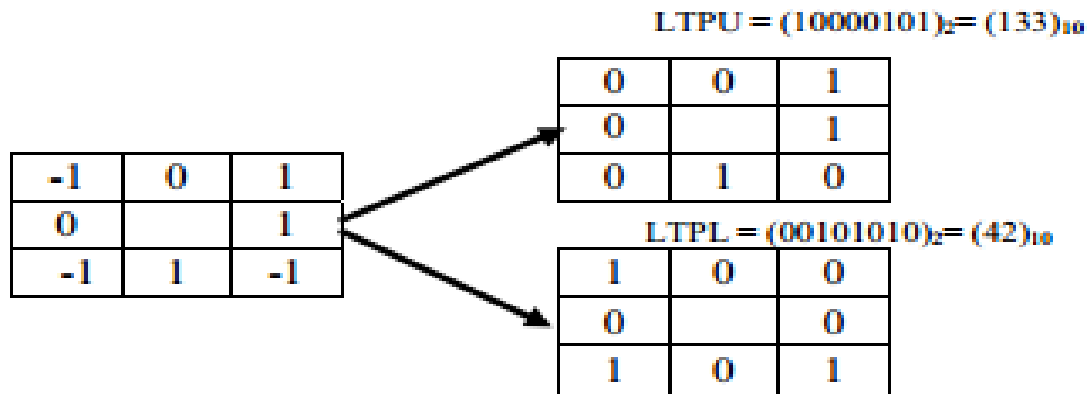


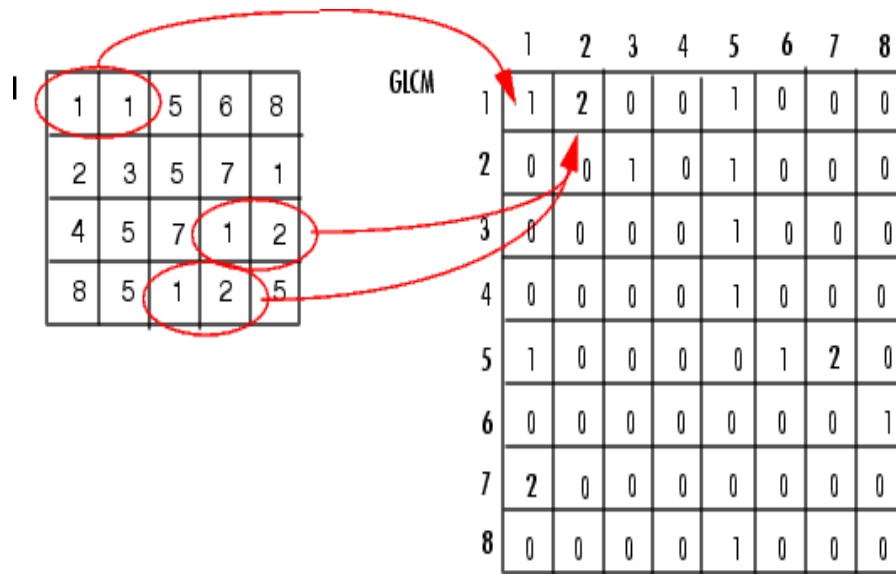
Fig. 4.4 Splitting LTP into two LBP channels

Gray-Level Co-Occurrence Matrix(GLCM)

Use the graycomatrix tool to create GLCM. The greycomatrix function produces a GLCM by measuring how strong the pixel (gray value) is from the spatial relationship given in the pixel value j. Spatial relationship between two pixels is automatically called as the interest pixel and the pixel to its right that are horizontally close, but another spatial relationship between the 2 pixels can be determined. Each item (i, j) in the final GLCM is the addition of the numeral of times a pixel has a value that I appear in a local relation given in pixel by value j in the input image. As the computer calculation necessitated for making the GLCM the most powerful image range is extremely expensive, graycomatrix scale image capture. Graycomatrix utilizes the design scales to reduce the amount of energy values in the gray image from values of 256 to eight. The GLCM rating is found by number of gray categories. To monitor the amount of gray levels in GLCM and strength values, use the function of graycomatrix's Levels and Gray Limits parameters. For more information, see the greycomatrix article.

The gray-level matrix matrix will reveal details about the local distribution of gray levels in the texture image. Eg, when most GLCM inputs are integrated next to the diagonal, the texture crawls in relation to a given offset. The diagram below shows how graycomatrix determines the first 3 values in GLCM. Since there is only 1 case in the input diagram where 2 adjacent vertical pixels having values 1 and 1, the element (1,1) of the GLCM output consists the value 1.

As there are 2 cases where two vertical pixels stand with the values one and two, GLCM (1,2) contains the number 2. Since there are no cases of two vertical pixels with values one and three, element (1,3) in GLCM has a value of 0. Graycomatrix continues to process the input signal, search for it in pairs of additional pixels (i, j) and to capture the amounts to the corresponding GLCM.



If you want to make more GLCMs, refer to the list of resources in the graycomatrix feature. This basis defines the pixel relationship of different levels of direction and time. For example, you can specify 4 directions namely the (horizontal, vertical, and two-dimensional) and four procedural steps in several sequences. In this example, the input image is displayed with 16 GLCMs.

This deletion is defined as the p-by-2 sequence of integers. Each row of the same members is a vector with two elements, [row set, column set], defined one set. The number of lines between the pixel of interest and its neighbor is represented by the line offset. The number of columns between the pixel interest and its neighbor is represented by col_offset. This example generates four-point and four-length removal for each directory. Once you have created GLCMs, you can use the graycoprops feature to draw various figures on them. This figures gives details regarding the image texture. Contrasts, Correlation, Energy and Homogeneity are figures that provide details about the image.

4.6 MORPHOLOGICAL PROCESS

The gathering of non-linear operations dealing with the shape or morphology of image features is called morphological image processing. Morphological operations, which depend solely on comparative positioning of values of pixel comparatively rather than numerical, are particularly suited to the

binary image processing. The Morphological operations may also be in addition to grayscale images to make the light transmission functions unidentified, and therefore making their absolute pixel values of less or no importance.

This Morphological techniques use a prototype or a small shape called a structuring feature to probe an image. The structuring function is placed in all the achievable image positions and is then compared to the respective neighbourhood of the pixels. Some operations determine whether the element is suited within the neighborhood, while other operations determines in the case of the elements that intersects with respect to the neighborhood.

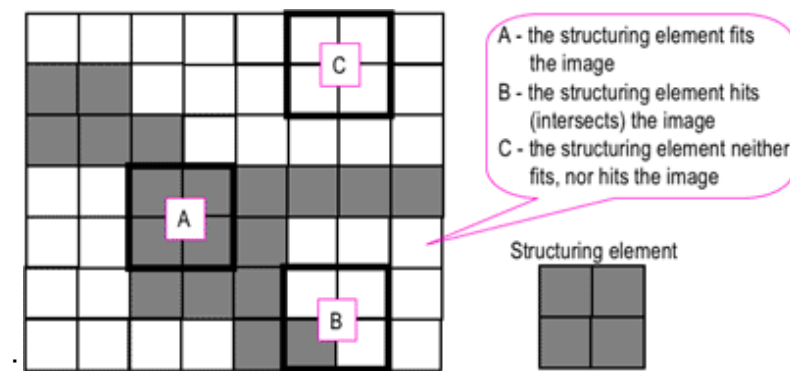


Fig. 4.5 Morphological Process

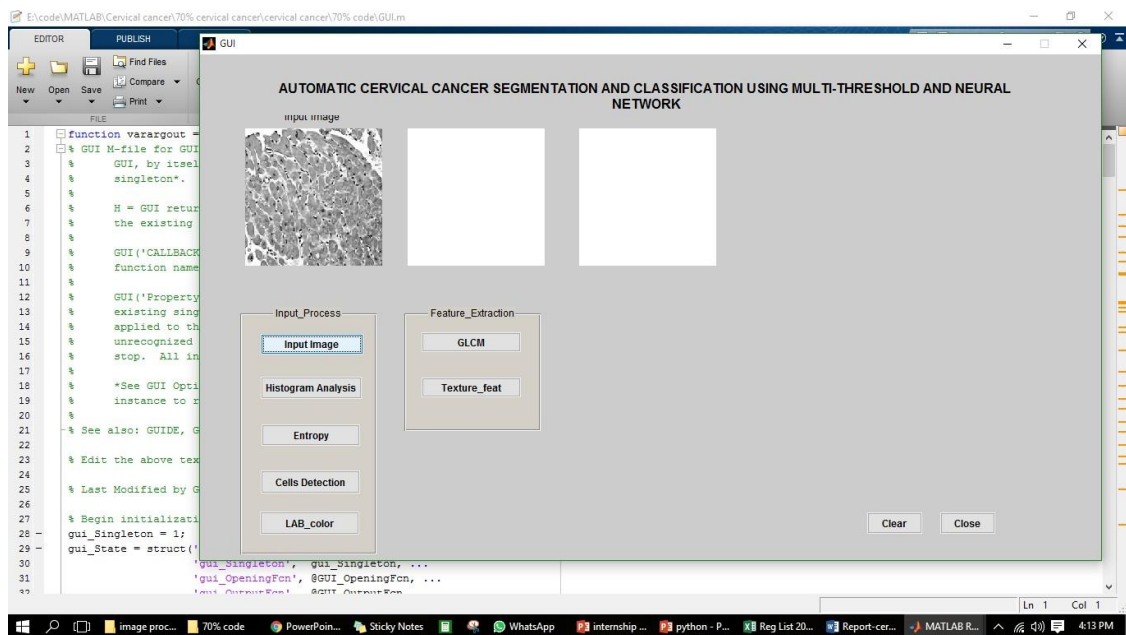
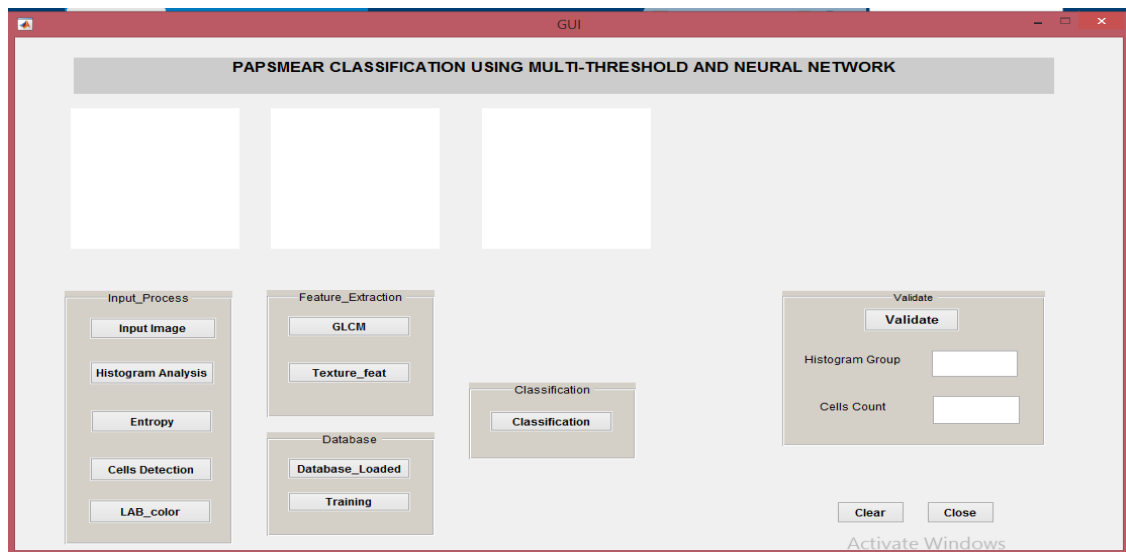
An picture is being probed with a structure type of feature. The morphological function that is performed on the binary image produces a new image where the pixel is having a value that is a non-zero. The image has a non zero value when the measurement of pixel is accurate.

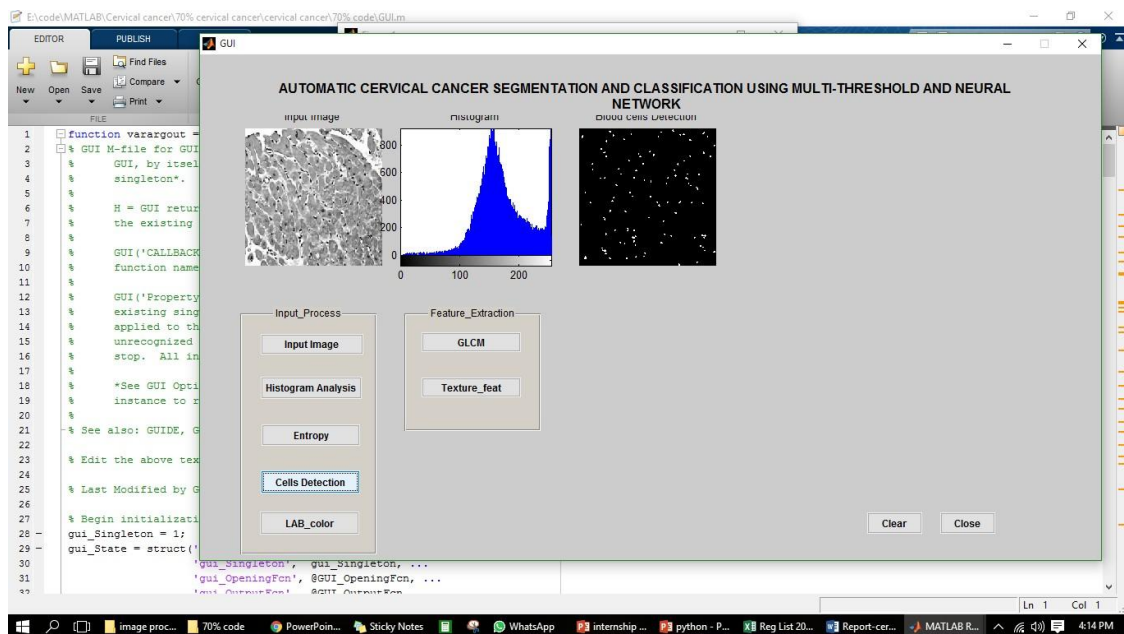
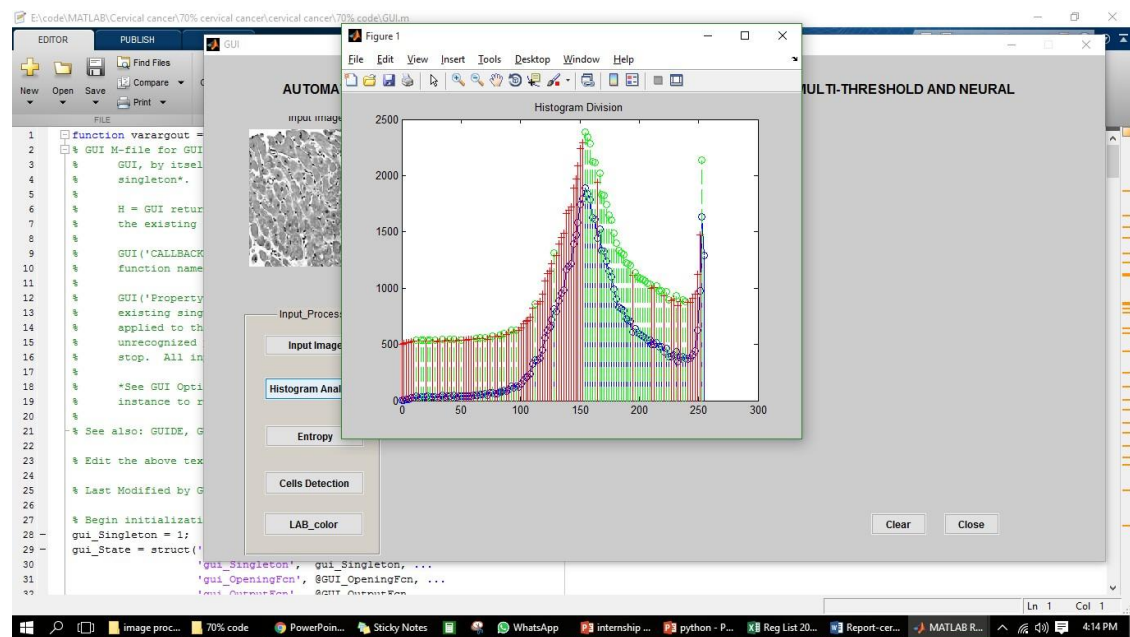
The main factor is a tiny binary image, or is a matrix of pixels whose values are ones or zeros.

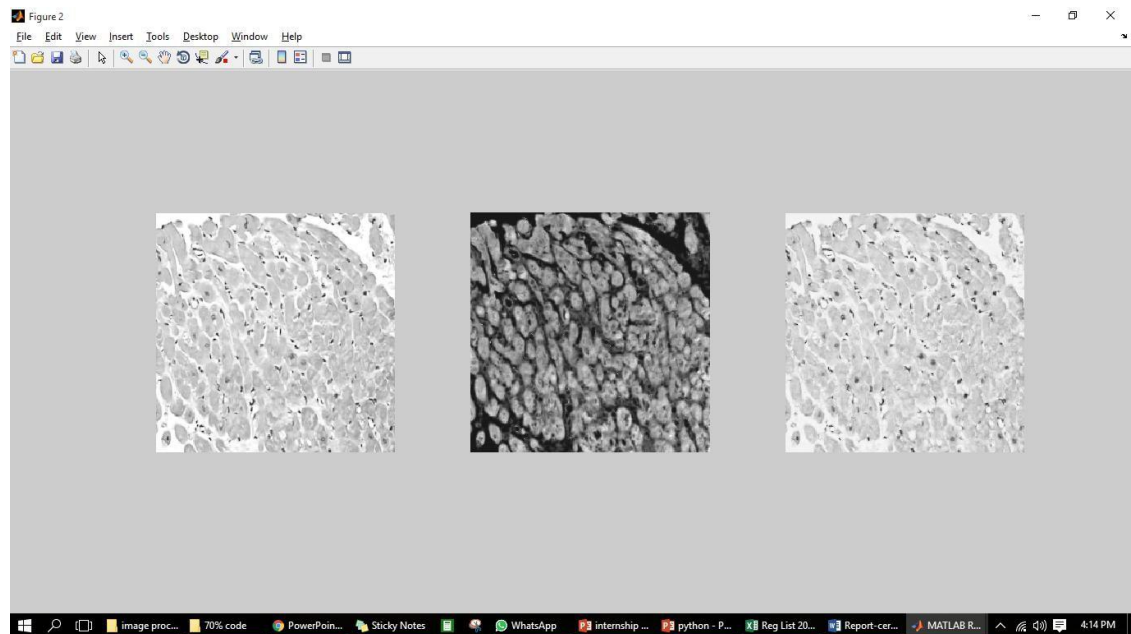
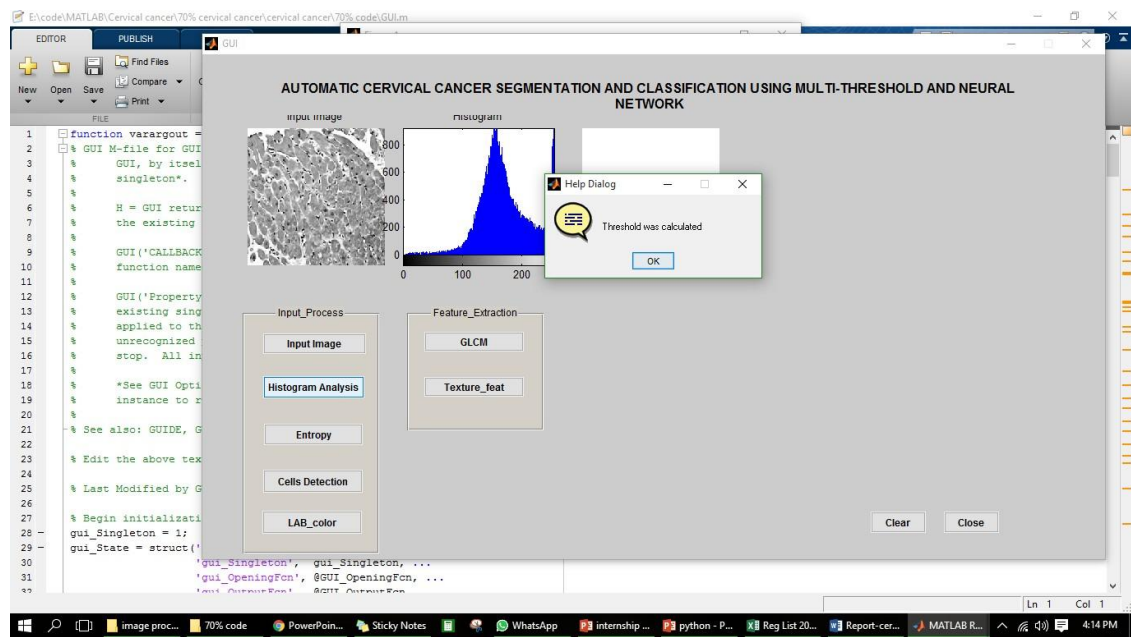
- The matrix proportions define the range of the structuring unit
- The matrix of zeros and ones defines its form.
- The root of a structuring part is normally one of its pixels, but it may also be outside the structuring element.

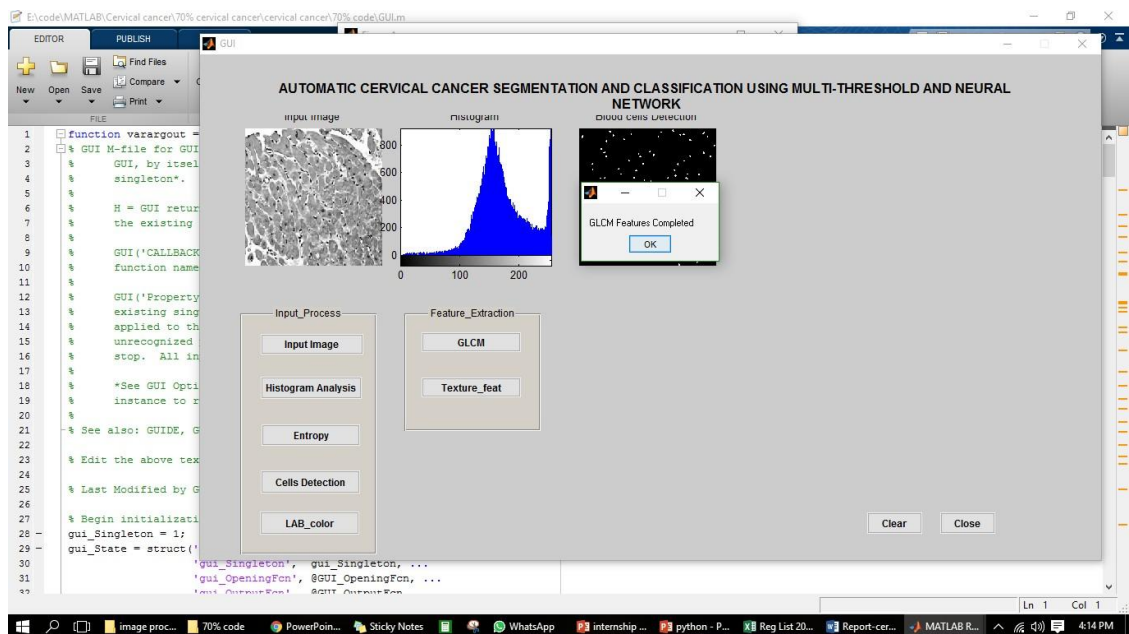
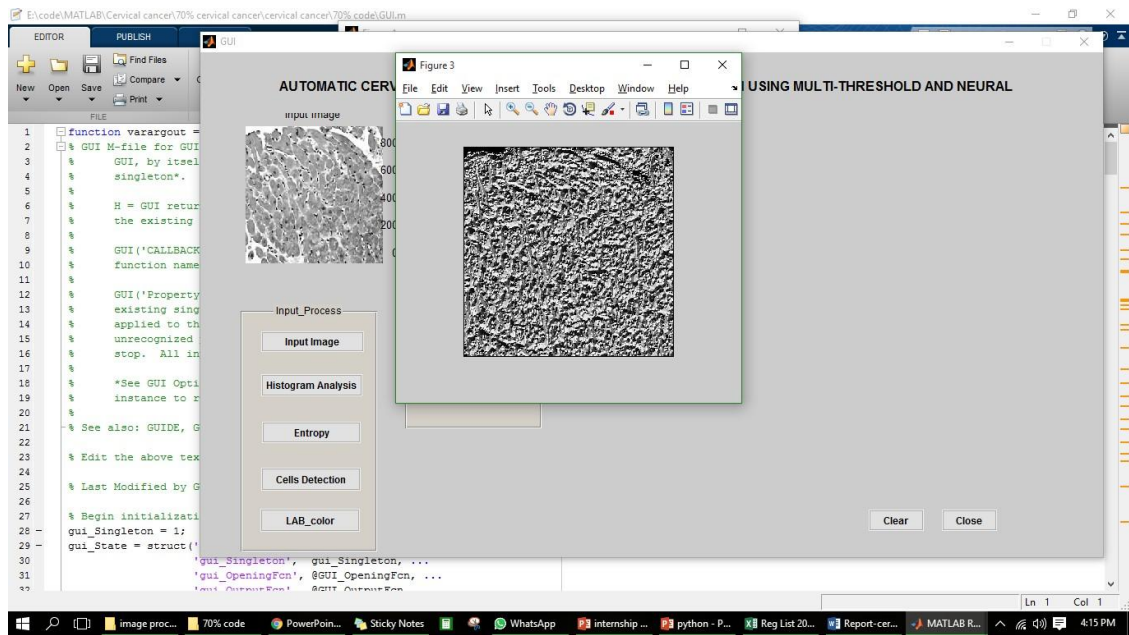
CHAPTER 5

RESULTS AND DISCUSSION









HISTOGRAM

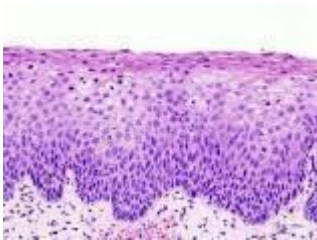
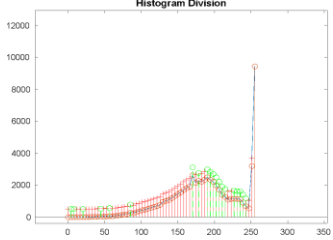
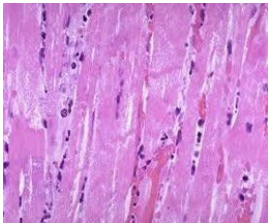
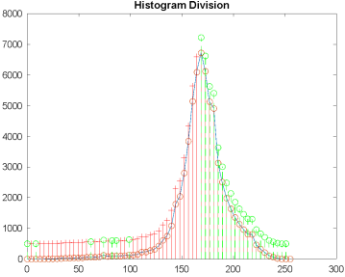
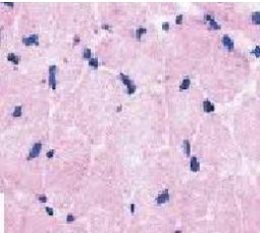
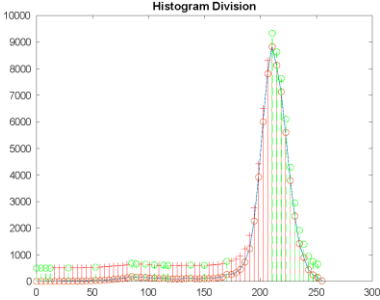
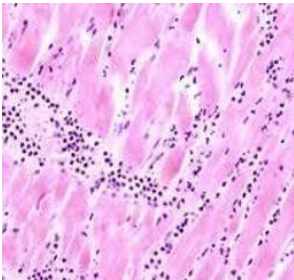
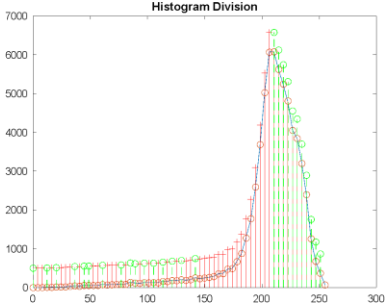
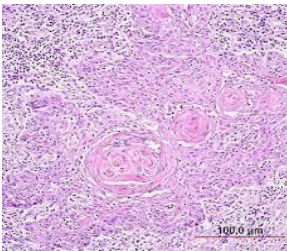
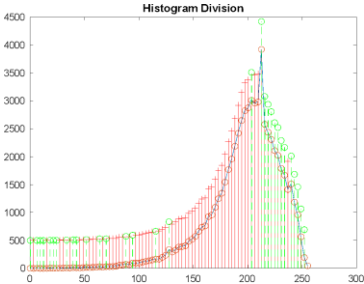
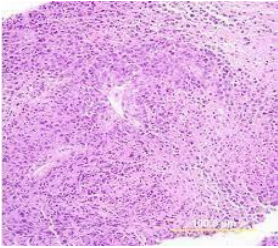
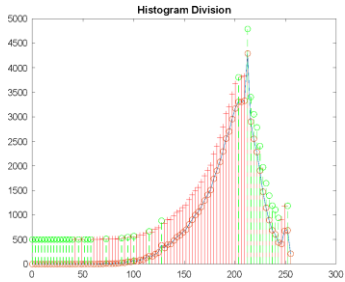
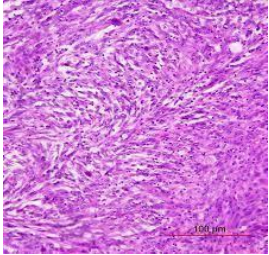
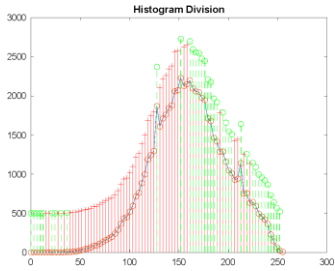
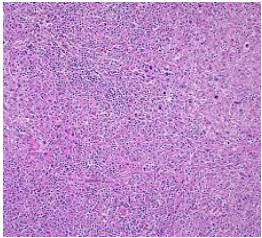
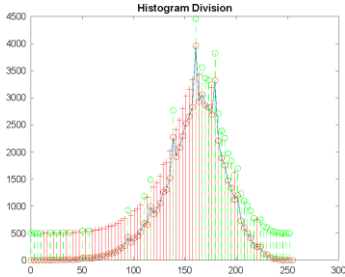
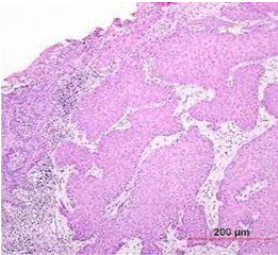
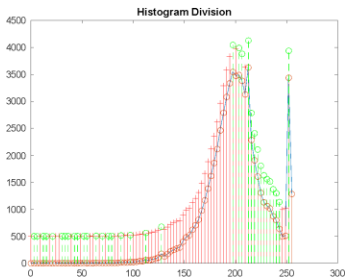
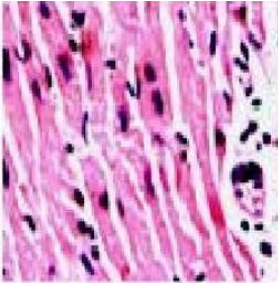
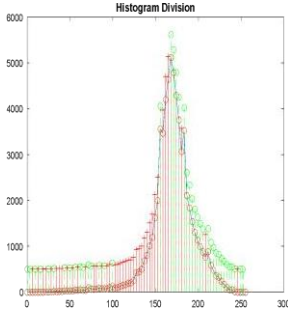
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IMAGE NO	INPUT IMAGES	HISTOGRAM
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ENTROPY

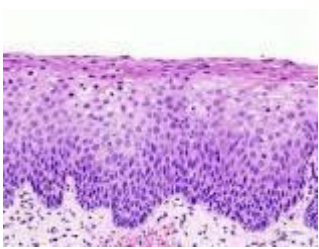
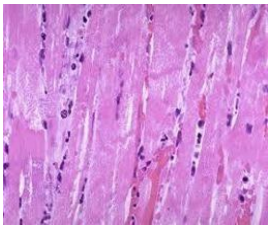
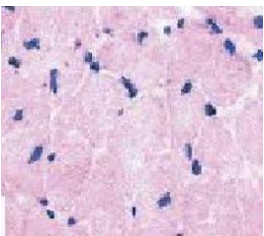
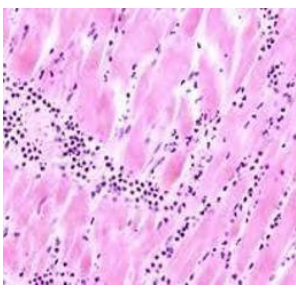
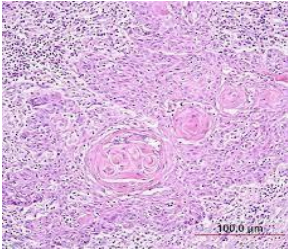
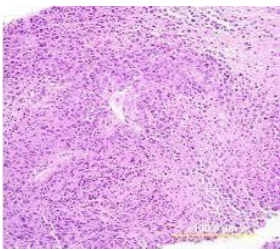
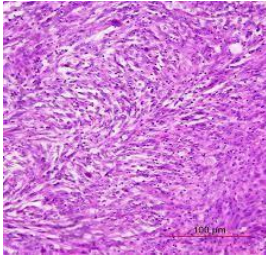
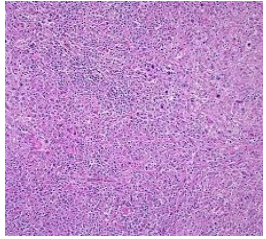
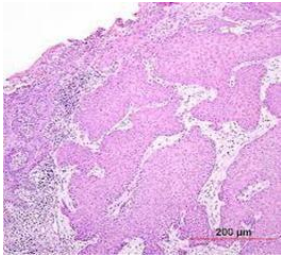
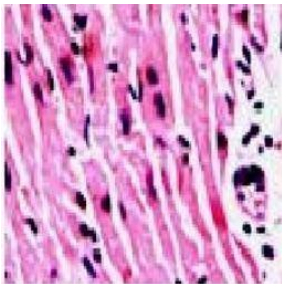
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CELLS DETECTION

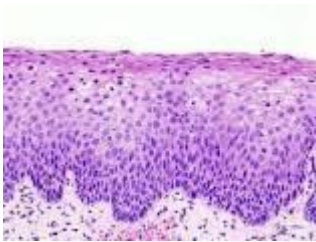
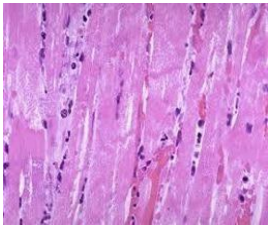
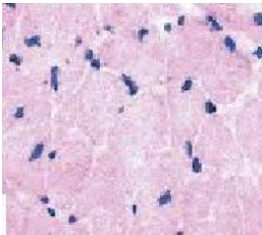
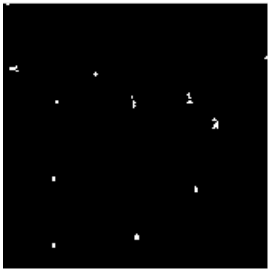
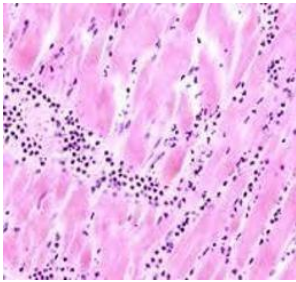
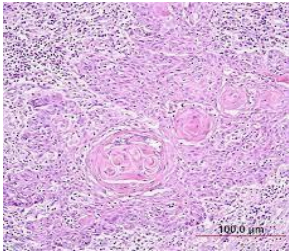
IMAGE NO	INPUT IMAGES	CELLS DETECTION
IMAGE 1		
IMAGE 2		
IMAGE 3		
IMAGE 4		
IMAGE 5		

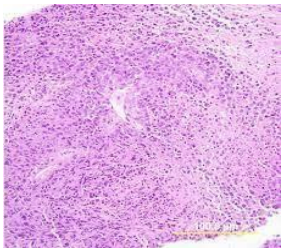
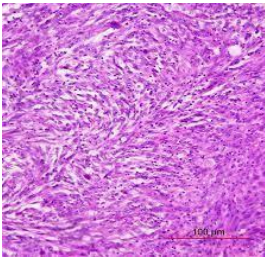
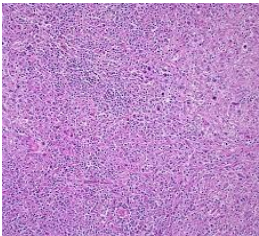
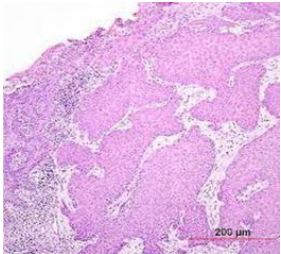
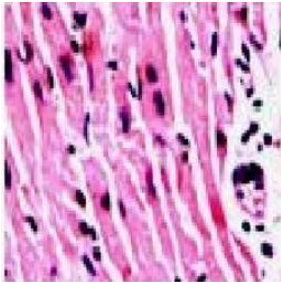
IMAGE NO	INPUT IMAGES	CELLS DETECTION
IMAGE 6		
IMAGE 7		
IMAGE 8		
IMAGE 9		
IMAGE 10		

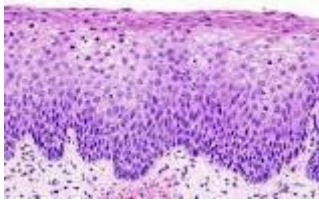
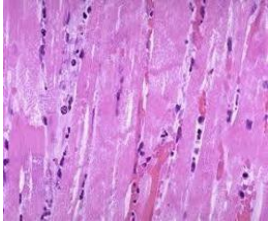
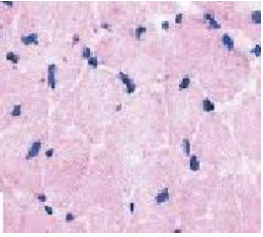
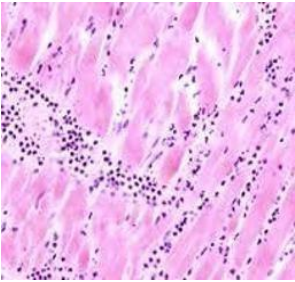
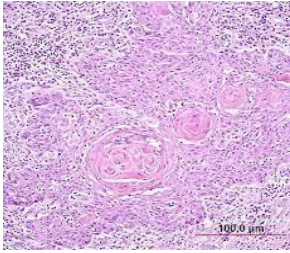
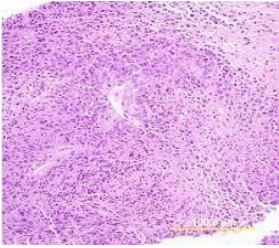
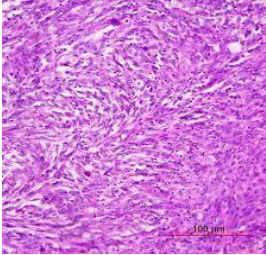
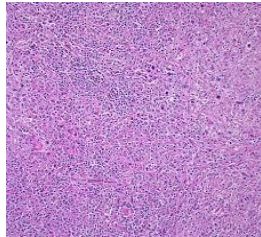
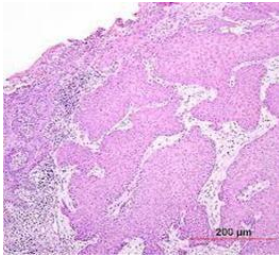
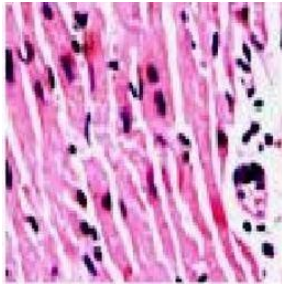
IMAGE NO	INPUT IMAGES	CELL COUNT
IMAGE1		66
IMAGE2		31
IMAGE3		16
IMAGE4		157
IMAGE5		18
IMAGE 6		0

IMAGE NO	INPUT IMAGES	CELL COUNT
IMAGE 7		1
IMAGE 8		6
IMAGE 9		4
IMAGE10		25

EXPLORE OF THE PROPOSED METHODOLOGY

IMAGE	ENTROPY	CELL COUNT	RESULT
1	14.654	66	ABNORMAL
2	16.569	31	ABNORMAL
3	13.584	16	ABNORMAL
4	13.722	157	ABNORMAL
5	13.967	18	ABNORMAL
6	12.543	0	NORMAL
7	12.654	1	NORMAL
8	11.852	6	NORMAL
9	12.534	4	NORMAL
10	14.552	25	ABNORMAL

CHAPTER 6

CONCLUSION AND FUTURE WORKS

Thus, image processing is used to recognize defects in MRI images, and a machine learning concept which is well known as neural network that is used for identification of cancer in the image. The test image features are removed in order to identify the images. The similar features will be derived from the data set images, and with the aiding of these features, we will be able to determine if the input image is normal or abnormal. The best type of detection is achieved based on the training that is given to the neural network.

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