EFFICIENT DIAGNOSIS OF CERVICAL CANCER USING DEEP NEURAL NETWORK

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Abstract
Women all around the world are affected by cervical cancer, which is a serious public health issue. Early detection and management can decrease the morbidity and mortality linked to this condition while increasing the likelihood of successful therapy. Hence, identifying women who are at risk of acquiring this condition requires the creation of accurate cervical cancer prediction algorithm. Accurate cervical cancer prediction models have been developed in recent years using Deep Learning (DL) techniques. This paper presents a simple novel method for identifying cervical cancer and shows the stage of the cancer whether lighter, moderate or severe. The Deep leaning algorithm Artificial Neural Network(ANN) is used to identify the stage of the cervical cancer.

***Key words:*** Cervical cancer, Clustering, Human Papilloma Virus(HPV), Artificial Neural Network(ANN).

I INTRODUCTION

Women all around the world are affected by the major health issue of cervical cancer. With an estimated 570,000 new cases and 311,000 fatalities worldwide each year, cervical cancer is the fourth most frequent malignancy in women, according to the World Health Organization (WHO). Many women are still identified with cervical cancer in its advanced stages, when treatment options are few and survival rates are dismal, in spite of the existence of reliable screening techniques and vaccines. For early detection and treatment, reliable and timely prediction of cervical cancer risk is essential.

Cervical cancer has been linked to a number of risk factors, such as HPV infection, smoking, immunological deficiencies, and chronic use of oral contraceptives. While some women without these risk factors may nevertheless be given a cervical cancer diagnosis, not all women with these risk factors will go on to get the illness. Hence, to identify women at high risk of cervical cancer, effective prediction models that combine numerous risk indicators must be developed. The severe stage of malignant cervix is seen in Figure.1.The ability to predict the risk of cervical cancer has recently showed promise thanks to developments in machine learning and data analysis approaches.

Deep Learning models analyze huge datasets that contain demographic, clinical, and genetic data to find patterns and associations that conventional statistical methods might miss. Deep learning algorithms can also gain knowledge from the past data and develop their predictions over time.
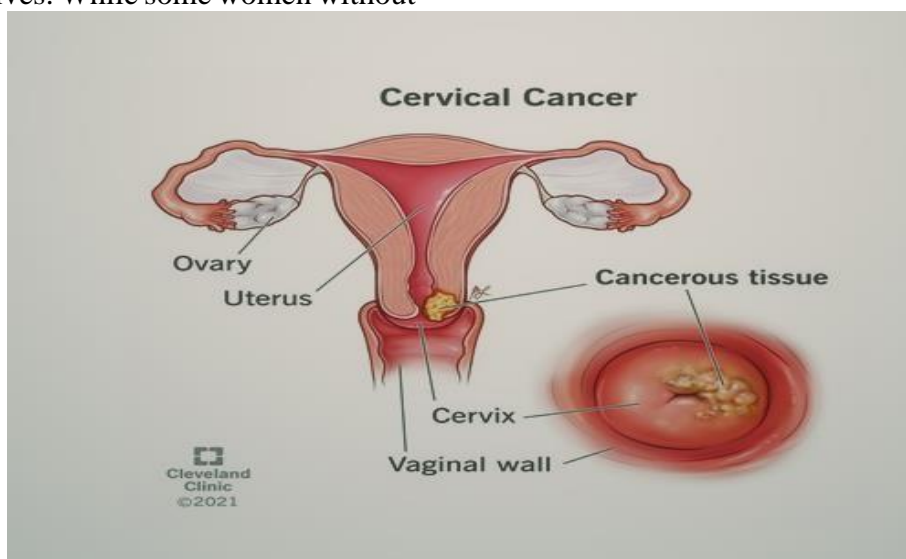
Figure.1 Cancerous Cervix

Proper risk assessment of cervical cancer can also guide women's individual screening and prevention plans. Women who are at high risk may benefit from more regular screenings or focused interventions, whereas women who are at low risk might just need screenings every few months or so. This strategy can lessen the impact of cervical cancer on women and society while making the best use of the scarce healthcare resources. The creation of reliable and precise risk prediction algorithms for cervical cancer is a current field of research.These models are probably going to get better and better at forecasting the risk of cervical cancer as more data become accessible and deep learning techniques advance.

II RELATED WORKS

NINA YOUNESZADE et al.2023 [2] discussed the architecture, opportunities, and Open Research Challenges in cervical

cancer diagnosis using Deep Learning methods. MD MAMUNUR RAHAMAN et al,2020 [10] discussed the comprehensive study of deep learning approaches for the cervical cytology image analysis and discusses the datasets , evaluation metrics for segmentation and classification along with existing methodologies for the analysis of pap smear cells.PAN HUANG et al, 2020 [3] discussed a technique of cervical biopsy tissue image classification based on Least Absolute Shrinkage and Selection Operator (LASSO) and Ensemble Learning-Support Vector Machine (EL-SVM). This article discusses challenges with artificial classification of biopsy tissue images during diagnosis and offers solutions.SUXIANG YU et al,2021 [6] discussed the method of four classification models CNN, SPP, Inception ,CNN +SPP+inception for performance evaluation and the comparison is done, which concludes that fourth model is best. In this real time datasets are used.

FAHDI KANAVATI et al,2022 [15] discussed the method to investigate the use of deep learning for the classification of whole- slide images of liquid-based cytology specimens into neoplastic and non neoplastic. This model is used for screening process of cervical cancer. MERCY NYAMEWAA ASIEDU et al, 2019 [9] discussed a method for automatic feature extraction and classification for acetic acid and Lugol's iodine Cervi grams and methods for combining features/diagnosis of different contrast in Cervi grams for improved performance. DAN XUE et al,2020 [12] discussed on classifying cervical histopathology pictures that are well, moderately, and badly differentiated using an Ensembled Transfer Learning (ETL) framework. FERNANDES KELWIN et al, 2018 [5] described a system for automated analysis of digital colposcopies and constructed a topology of issues and solutions, highlighting each

one's salient features, benefits, and drawbacks. highlighted the open issues in the field and published a database that acts as a standard framework for assessing such systems.

YUEXIANG LI et al, 2020 [1] discussed a method of a deep learning framework for the accurate identification of LSIL+ (including CIN and cervical cancer) using time-lapsed colposcopy images.

III EXISTING WORK

An essential step in the diagnosis of cervical cancer is a cervical biopsy. It is challenging to artificially classify biopsy images for diagnosis, and pathologists' clinical expertise is needed. Computerized biopsy tissue images of lesions that are identical to one another have low classification accuracy and can only determine if a cell is cancerous or not.

3.1. Existing Clinical Methodologies For Cervical Cancer Prediction

a) Pap Smear test

The pap smear test, which has been used for 60 years and has greatly lowered the death rate from cervical cancer, is shown in Figure. 2. Cells from the squamocolumnar terminal of the cervix are normally removed with a brush or spatula and spread onto glass slides for the test. Cytotechnologists examine the glass slides under a light microscope to identify whether the cell is malignant, enabling an early and effective course of therapy. The length of the screening operations varies from 5 to 10 minutes, depending on how difficult the cell orientation is. A cytotechnologist cannot evaluate more than 70 samples in a single day. This approach likewise needs constant, undivided attention to make sure no cancerous cells are overlooked.
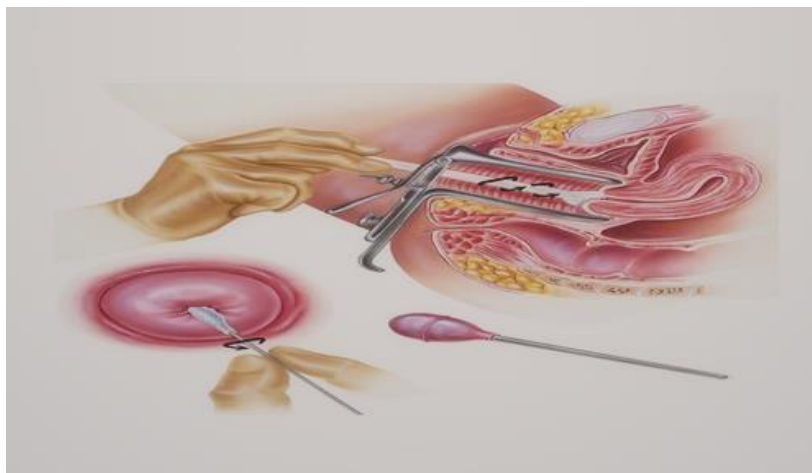
Figure.2 Pap Smear test

a) Diagnosis of colposcopy images using deep learning

The use of DL approaches in medical image analysis, which is now the most popular and successful subset of machine learning algorithms, is not an exception in the analysis of cervical cytopathology images. In this sector, Artificial Neural Networks (ANNs) are frequently used as deep architectures and have had outstanding success with cell detection, segmentation, classification, and extraction of the region of interest (ROIs). To accurately classify the cells as normal or abnormal and tells the stage of the cervical cancer

IV PROPOSED WORK

The goal of this paper was to create a computer-aided cervical cancer diagnostic model that was incredibly accurate. The consistency and accuracy of cancer diagnosis are improved using Artificial Neural Network algorithm. In this, we forecast the cervical cancer progression stages as in figure 3.
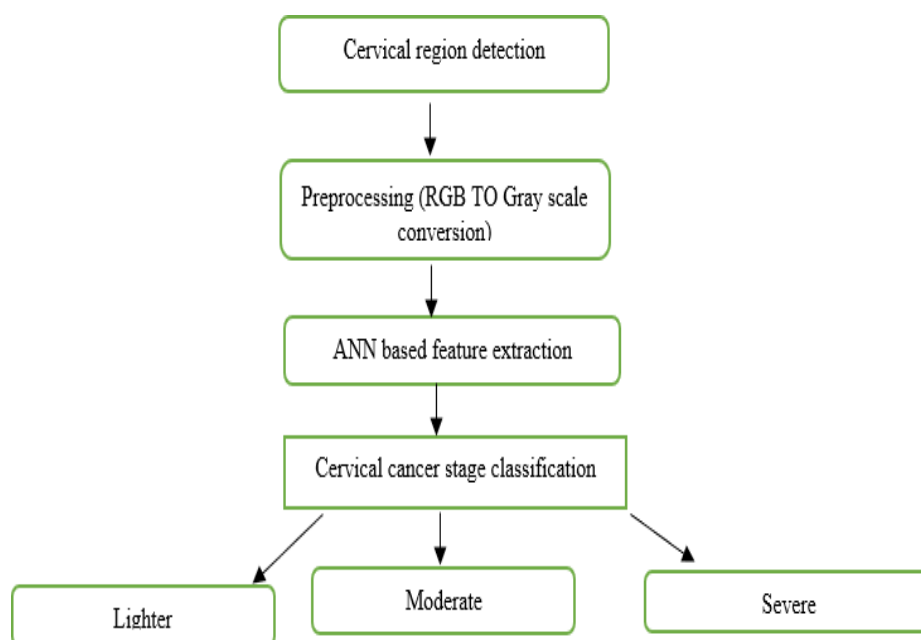
Figure.3 Flow diagram to detect the cervical cancer

4.1. RGB to grayscale conversion

RGB to grayscale conversion is a common image processing operation used to convert an RGB (Red, Green, Blue) image to a grayscale image which is shown in Figure.4 A grayscale image contains only one information channel, while an RGB image contains three information channels. There are several ways to perform RGB to grayscale conversion, but one of the most common is using the lightness method. The lightness method calculates a grayscale value for each pixel based on a weighted average of the three color channels. Weights are based on the perceived lightness of each color. where R, G, and B are the red, green, and blue color channels of the RGB image, respectively. The values for the coefficients 0.2126, 0.7152, and 0.0722 are derived from the perceived luminance of each color, based on the NTSC (National Television Standard Committee) standard for color television. To perform an RGB-to-grayscale conversion, iterate through each pixel in the RGB image and use the lightness method to compute the grayscale value for that pixel. The resulting grayscale image has only one channel of information, and each pixel represents the intensity or brightness of the corresponding pixel in the original RGB image (Figure 4).
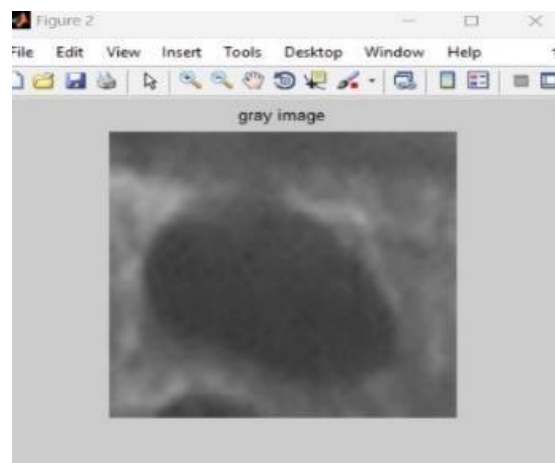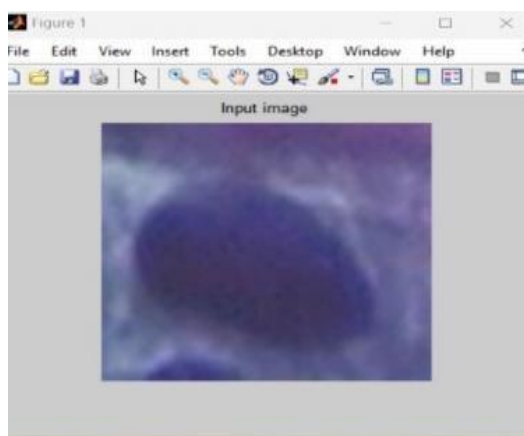
Figure.4 RGB to Grayscale conversion

4.2. Feature Selection

GLCM (Grey level co occurrence matrix) also known as grey level spatial ependence matrix feature is used for image analysis. They will extract the patches or portion of the image with the pixels that is pair of pixels after extract the image we put that image for training the algorithm like Artificial Neural Network(ANN).

In this paper we use following properties for image classification,

1.Contrast

2.Correlation

3.Energy

4.Homogeneity

4.3.K-Means Clustering

Supervised Deep learning method K-means clustering is used to arrange data points into clusters based on their similarity. K-means clustering can be used to find patterns or groups of cervical cancer patients who share similar traits or risk factors. It is a vector quantization technique that was first used in signal processing and is widely used in data mining for cluster analysis. K-means clustering seeks to divide n observations into k clusters, where each cluster serves as a prototype for the cluster and each observation belongs to the cluster with the nearest mean. We must first choose a set of features to be used for

clustering before we can apply k-means clustering to the data related to cervical cancer. After choosing our features, we can use k-means clustering to put the patients into groups based on how similar they are. When using k-means clustering, data points are iteratively assigned to the closest cluster centroid, which is then updated depending on the mean of the data points in each cluster. The algorithm must be executed after determining the k number of clusters. Nonetheless, k-means clustering can be a helpful technique for spotting trends or classifying patients according to shared traits. In this the input image is divided into three clusters which is shown in Figure.5.
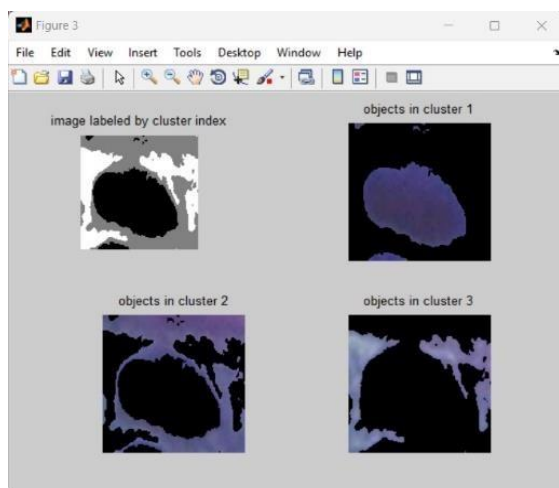
Figure.5 Clusters

### 4.4. Artificial Neural Network (ANN)

Machine learning algorithms known as artificial neural networks (ANNs) are frequently employed for categorization problems. The structure and operation of the organic brain network serve as the foundation for architecture (figure 6). The neurons of ANN are arranged in several layers, just like the neurons in the brain. A common type of neural network is the feed-forward neural network, which has three layers: an input layer for receiving outside data needed for pattern recognition, an output layer for providing the solution, and a hidden layer that acts as an intermediary layer between the other layers.
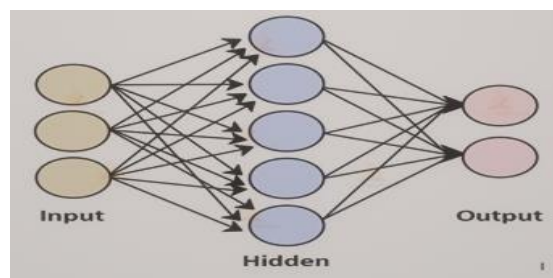
Figure 6. Architecture of ANN

### 4.4.1 Working and Training of ANN

The input layer is where the information is first fed. Following that, it is transferred to the hidden layers, where an interaction between these two layers first assigns weights to each input at random. The weight total, which is a combination of weights and bias, is then passed through the activation function once bias has been added to each input neuron. The duty for choosing which node to fire for feature extraction and final output calculation falls on the activation function. As a result, this entire process is referred to as forward propagation. Finally, after an output model is built to compare with the original output and the error is known, the backpropagation weights are updated to reduce the error, and this process continues for a specified number of epochs (iterations). increase. Finally, the model weights are updated and predictions are made. A dataset containing patient data and the related cervical cancer diagnosis would be required in order to train the ANN. It would be necessary to separate the dataset into training, validation, and testing sets. The training set would be utilized to fine-tune the ANN's weights, the validation set would be utilized to tweak the ANN's hyperparameters, and the testing set would be utilized to assess the ANN's performance on unlabeled data. The ANN can be used to predict if new patient data reveals the existence of cervical cancer once it has been trained. In this the first cluster image (figure 7).is taken and they are deeply analyzed and the stage of the cancer is predicted (figure 8- figure 11).
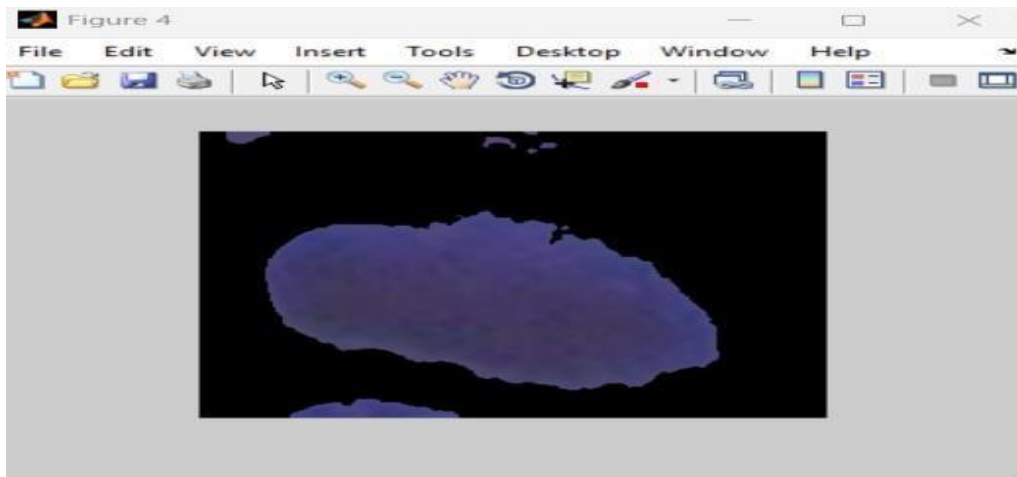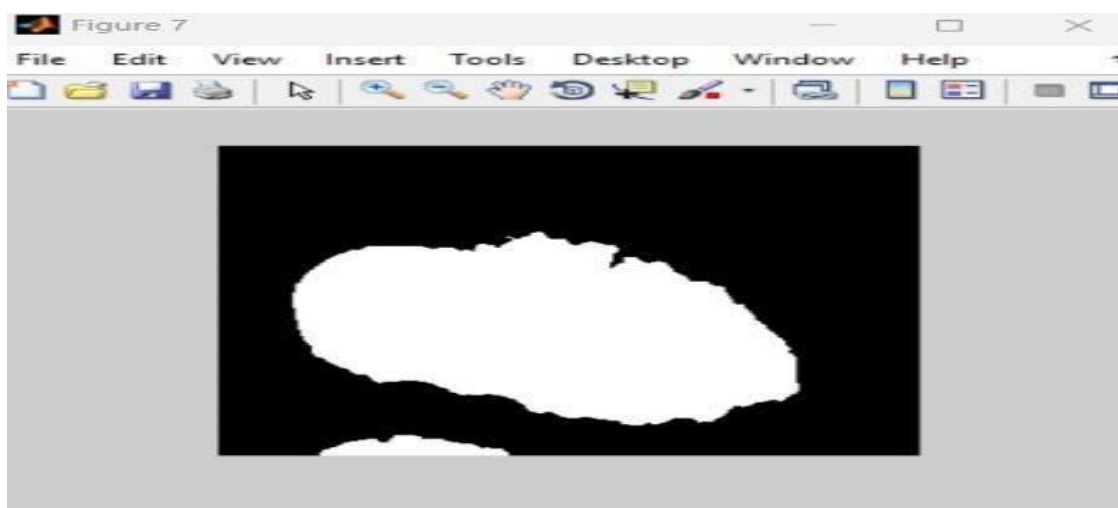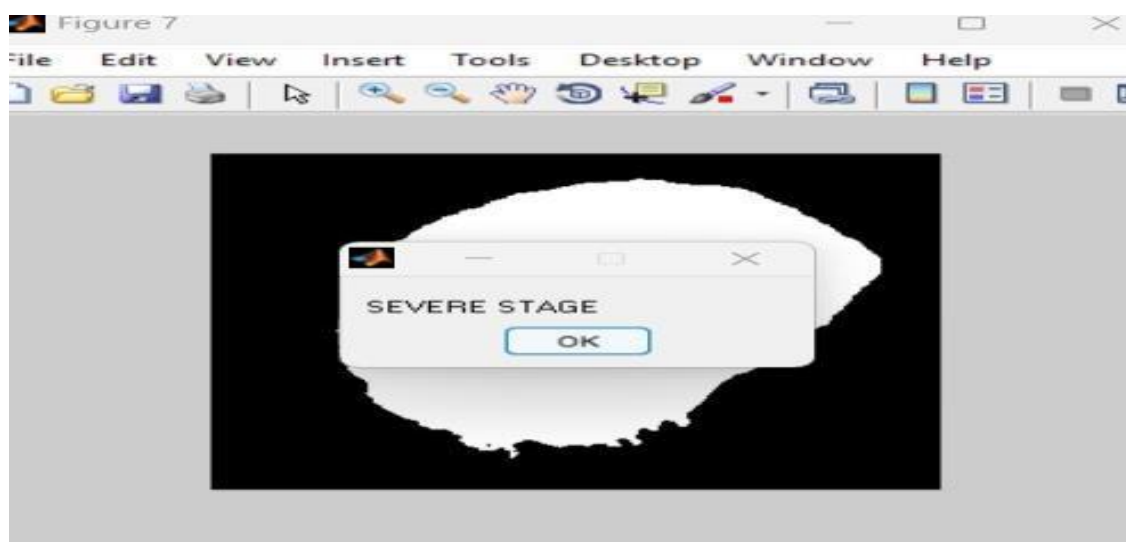
Figure 7.First cluster
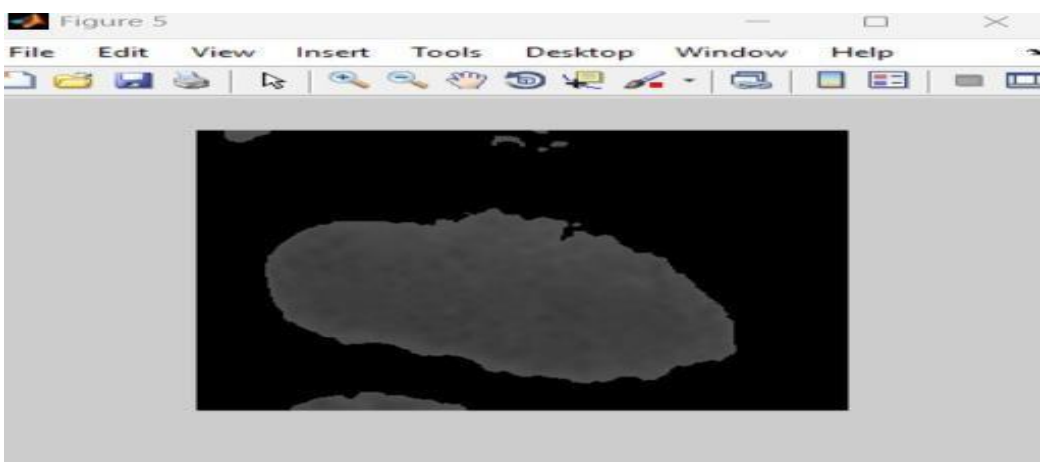
Figure 8. Analysing the feature and deeply classifying the cell
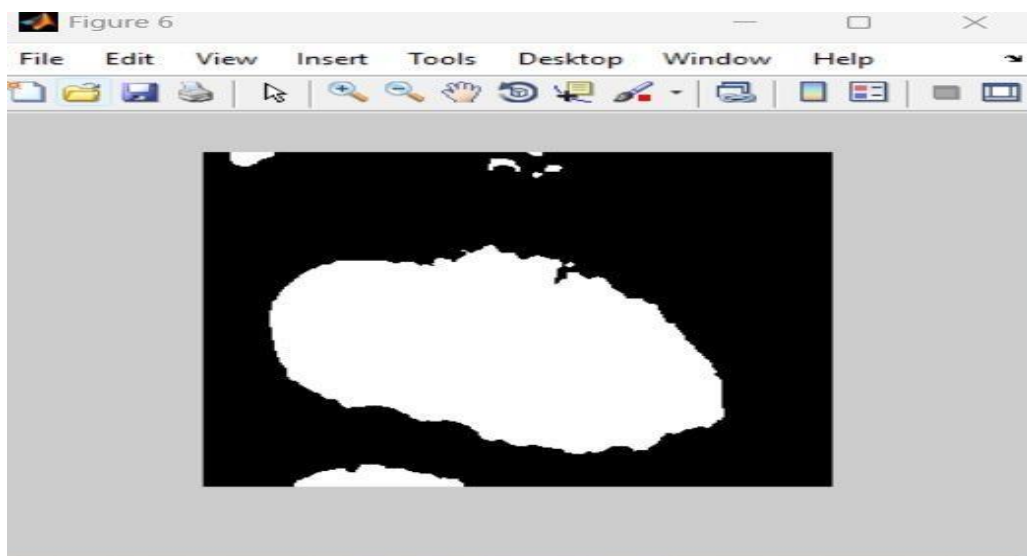
Figure 9.Gray Scale conversion

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1795

Figure 10. Noise Cancellation

Figure.11 Identifying the stage of the cancer

V EVALUATION METRICS

We used the following criteria to assess the effectiveness of our model. The values of the properties are displayed in Table 1 using GLCM features.

Table 1 Values of the properties

S. No.	Properties	Value
1.	Dissimilarity	3.348651960784 31e-02
2.	Homogeneity	9.859221813725 49e-01
3.	Entropy	9.055881656303 044e-01
4.	Standard Deviation	1.404392671575 501e+01
5.	Mean	2.255688476562 500e+01

VI EXPERIMENTAL AND ANALYSIS

We could give the cervical cancer image as the input , it deeply classify the image and tells the stage of the cancer and also provide the values of the properties in which they are classified.
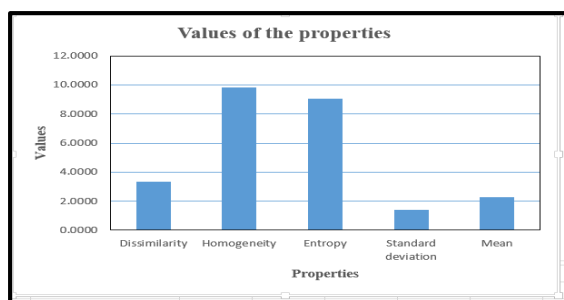
Figure.12 Value of Properties

In this the value of Entropy and Homogeneity is 9.0 and 9.8 respectively (as in figure 12). when the value of entropy and homogeneity is greater than 5 the code is effective and successfully identify the stage of the cancer.

VII. CONCLUSION AND FUTURE WORK

Here the Deep learning algorithm like Artificial Neural Network(ANN) is used for the cervical cancer detection and it's stage. From the Table 1 we knew that the values of Entropy and Homogeneity is greater than 5 i.e) 9.0 and 9.8 respectively , as we know in GLCM feature if the values of Entropy and Homogeneity is greater than 5, the code will be efficient. In future, We will use another Deep Learning algorithm like Convolutional Neural Network(CNN) and increase the values of the properties in future.

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