



BRAIN TUMOR DETECTION AND CLASSIFICATION USING SVM AND CNN FROM MRI SCANS

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Abstract

Human body has of several organs and among them the brain is the most critical organ in the body to regulate and control all important tasks done by human being. Sometimes due to over production of cells in brain may cause abnormal tissue which are infectious or non-infectious. The infected part is called cancerous tumour which will slightly spread in the brain or other parts of the body. But till to the date it is not found the real cause of the tumour development in the brain. But it is found that medical cases on brain tumour have not reduced, according to the research 1.8% of the population diagnosed by tumor. There are two types of brain tumours, namely benign and malignant. Benign is type of tumour which will not spread other parts of the brain or body whereas Malignant will spread other parts of the body or within the brain. So it's important to detect the tumors early as possible, so that early treatment can be planned which will reduce the overall death rate around the world.

For the monitoring of brain tumour diagnosis, the research suggested a computer-assisted radiology system that will analyze brain tumor using MRI data. DWT and GLCM procedures are used to extract features, and CNN, SVM algorithms to classify tumours with excellent accuracy.

The project consists of a few models to detect and classify the MRI scans and models will segments pictures and extracts features using discrete wavelet transform and Gray level co - occurrence to accurately classifying tumours using SVM and CNN with a good accuracy.

KEYWORD: MRI scans, GLCM, DWT, SVM, CNN

1. Introduction

The human body has several vital organs like Heart, Brain, Kidney, Liver etc.,. These organs made up cells, which are building blocks of the body. When these cells grow and divide more than expected or they do not die when they are suppose to, it forms an abnormal mass called as Tumor. Diagnosis of these tumor is crucial part and internal organ's tumorous part cannot be seen bare eye so there are several methods to capture, such as PET (Positron Emission Tomography), CT (Cypher Tomography), ultrasound, MRI (Magnetic Resonance Imaging), Spectroscopy, Fusion, and others, can be used to detect brain tumors. MRI is preferred because it effectively detects the following conditions: lumps, tumour, bleeding, swelling, or infections. One of the most difficult challenges in medical analysis is the separation of exact position of from the scans that is called segmentation. This further associates the borders of objects such as aberrant regions or organs. The segmentation approach yielded beneficial results in conveying properties of the segmented tumour region such as area, bounding box, curiosity and aspect. The goal of our research is to directly detect as well as categorize brain outgrowths using a variety of methodologies including medical image processing, pattern analysis, and computer vision for brain disease refinement, segmentation, and classification. Neuroscientists, radiologists, and other medical practitioners can use this technology and easy to use and study about the case. Pre-processing of MRI images obtained from online cancer imaging libraries, as well as evaluations obtained from different pathology laboratories, is involved in these techniques. The method is expected to improve the current brain tumour detection and perhaps minimize health care expenditures by minimizing the need for follow-up surgeries.

1.1 Dataset Used for Analysis

Dataset collected from Kaggle which has wide number of MRI scan collections and also from other online resources. The dataset used in this project is purposely divided into two folders namely Malignant and Benign. And total number of images used for this project is **1220** Images which is total number of images in both folders.

Data was collected from various verified sources and so segregated into two types:

- Malignant (Cancerous)
- Benign (Non-cancerous)

2. System Design

The figure 1 depicts the various phases of the system's development. The interaction between the different application components is depicted, along with where they fit into the development hierarchy because every module in the chosen issue functions separately.

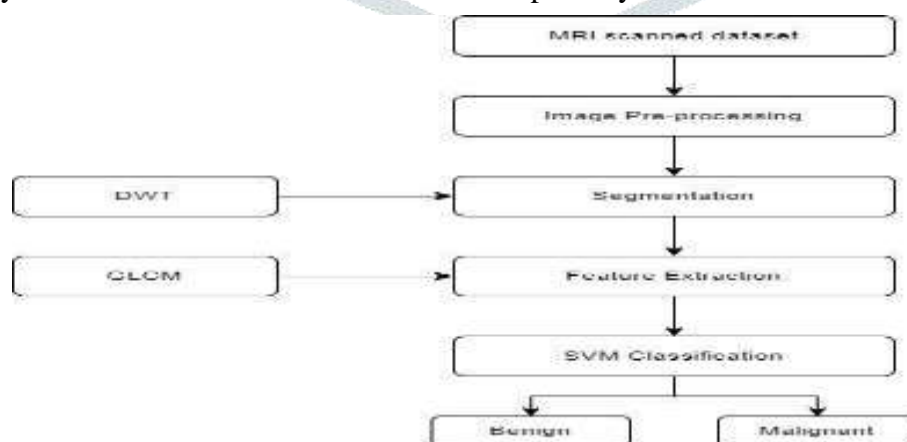


Fig 1 System Design for SVM

MRI scanned dataset: This is the first stage of the project. At this stage images are collected and stored at the local device for training purpose. All images are collected mainly from Kaggle website as well as other internet sources. Kaggle has rich number of datasets and available for research purpose.

Image Pre-processing: Preprocessing is nothing but improving the image data by suppressing it without any loss in details. Images must be preprocessed for better and fast calculation. Hence the MRI scanned images must also be preprocessed. Most of the MRIs are noiseless or low noise.

2.1 Segmentation: often based on the properties of the picture's pixel, image segmentation is widely used method in digital image preprocessing and analysis to divide an image into various parts or areas. Foreground and background can be distinguished in an image using segmentation, and pixels can be grouped together according to their similarity in color, shape, position. Segmentation is nothing but extracting the abnormal part that is tumor part from MRIs. This is very complicated and crucial part of the project. Hence, in this project Discrete Wavelets Transforms are applied on the images.

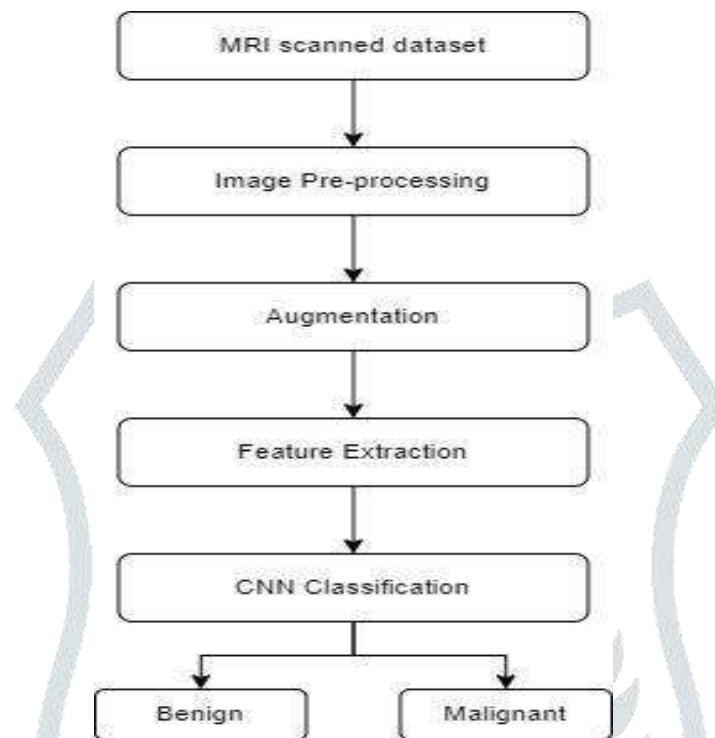


Fig 2 Block diagram for CNN

2.2 Feature Extraction: Features of the images plays a vital role in the image classification and are easy to understand by the machine learning methods. The process of translating raw data into numerical features that may be processed at the same time it keeps the information in the original data set is referred to as feature extraction. It produces better outcomes than merely applying machine learning to raw data

The fig5.2 depicts the design for CNN; Classification is the process of classifying a set of datasets into specified classes. It may be done on both structured and unstructured data. Predicting the class of provided data points is the first step in the procedure. The classes are also known as the goal, label, or categories. The classifier will classify between Benign or malignant.

3.Methodology and Implementation.

3.1 Preprocessing

The filter is applied to smoothen the image to remove the noise.

1. Intensity gradients of the image can be calculated.
2. Double threshold will be applied to determine potential edges.
3. So at last the detection of edges will be finalized by suppressing other edges and are weak and not connected to strong edges.
4. Brain tumour segmentation refers to the process of identifying tumour tissues from normal brain tissues and tumours using MRI images or other imaging modalities. Its mechanism is based on identifying similar subjects within an image and grouping them

together by either finding the similarity measure between the objects and grouping the objects with the greatest similarity or finding the dissimilarity measure between the objects and separating the most dissimilar objects within the space.

3.2 Feature Extraction:

3.2.1 Discrete Wavelet Transform (DWT)

The benefit of using dyadic locations and Scales, among many wavelet the potential wavelet form is discrete wavelet transform. The following is an introduction to DWT's fundamentals if the square-integral function $x(t)$, then its wavelet transform (WT) with respect to a wavelet (t) in particular is defined as

$$W_{\psi}(a, b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{b}\right)$$

The mother wavelet is mentioned as $\psi(t)$ and is used to calculate the wavelet $\psi_{a,b}(t)$ here, the dilation factor b is a translator parameter. Wavelets come has a variety of forms that have grown in significance as wavelet analysis has progressed. The most significant wavelet is the Haar wavelet, which is the most straightforward and frequently used wavelet in many applications.

3.2.2 GLCM (Gray Level Co-occurrence Matrix)

GLCM is a used for classifying and analyzing medical images. This technique reveals the relative location of two pixels in relation to one another. Then, the number of pixel pairs occurring at a specific distance is counted to form the GLCM. A distance vector $d=(x,y)$ is constructed to calculate the GLCM matrix for an image $f(a, b)$. The chance that grey levels a and b occur at distance d and angle is specified as the (a, b) th element of the GLCM matrix P , which is then used to extract texture characteristics. To construct the co-occurrence matrix, four angles (0, 45, 90, 135) and four distances (1, 2, 3, 4) can be employed. GLCM is a commonly used technique for classifying and analyzing medical images.

3.3 Classification

3.3.1 Support Vector Machine (SVM)

Support vector machines are a type of supervised learning model as well as related learning methods SVM also used in classification analysis to examine data and identify distinct patterns. The basic SVM is a non-probabilistic binary linear classifier that takes a collection of input data and predicts which of two potential classes, malignant and benign, will form the output for each input. Using the collection of training examples that have been identified as belonging to one of the two categories. An SVM training approach creates a model that classifies new instances into one of the two categories. An SVM model is a mapping of cases as points in space, with as much space as possible between the examples of the various categories. SVM model is a mapping of cases as points in space with as much space as possible between examples from different categories. Then, fresh instances are mapped into it, and they are anticipated to belong to a category based on which sides of the gap they fall

A support vector machine generates a hyperplane or collection of hyperplanes in a higher- or infinite-dimensional space that may be used for regression, classification, prediction or other tasks.

3.3.2 Convolutional Neural Networks (CNN)

Convolutional neural networks are made up of neurons with biases and weights that may be learned, much like conventional neural networks. Each neuron takes in a number of inputs and weights then sends the result via an activation function to produce an output.

A multilayer perceptron, the CNN algorithm is specifically designed for identifying two-dimensional picture information. Input, sample, convolution, and output layers make up this layer structure.

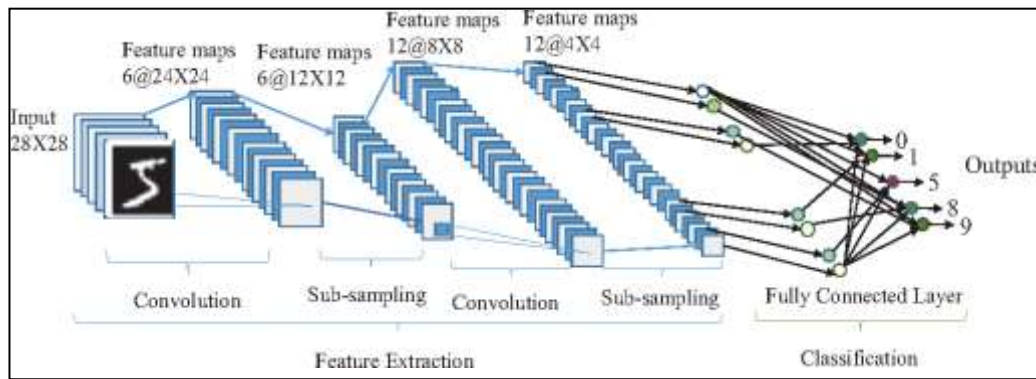


Fig 3 CNN Block Diagram

3.2.3 Residual Network (ResNet-50)

A Convolutional Neural Network is a well-organized deep learning machine learning method. Numerous varied picture sets are used to train CNNs. Convolutional neural networks are built to learn rich features for a variety of pictures from the databases. In many cases, these feature representations perform better than manually created features like HOG, LBP, or SURF. When CNN is pre-trained for feature extractor it is simple approach to take use of CNN capabilities without spending time and effort on training.

Residual networks are convolutional neural networks with 50 layers, like the well-known ResNet-50 model. Machine learning specialists add extra layers while using deep convolutional neural networks to address a computer vision challenge. Meanwhile the various layers are trained for a many kinds of tasks to produce highly accurate outcomes and these extra layers which is compared with regular neural networks aid in the more effective solution of complicated problems. Although the number of many layers might enhance the model's characteristics, a deeper network can disclose the problems of degradation.

While ResNet allows flexibility of adding additional layers to CNN to handle increasingly challenging computer vision jobs, it also has a number of drawbacks. With more layers added, it has been shown that training neural networks gets more challenging, and in certain situations, accuracy decreases as well.

Here, the utilization of ResNet becomes significant. Training increasingly complex neural networks is more challenging. ResNet makes it feasible to overcome the challenges of training extremely deep neural networks.

The project uses a multiclass linear SVM trained with CNN features derived from the pictures in the dataset. This method of categorizing photos refers to the accepted practice of using characteristics taken from images to train a pre-built classifier. Here, however, features are retrieved using a CNN rather than picture features like HOG or SURF.

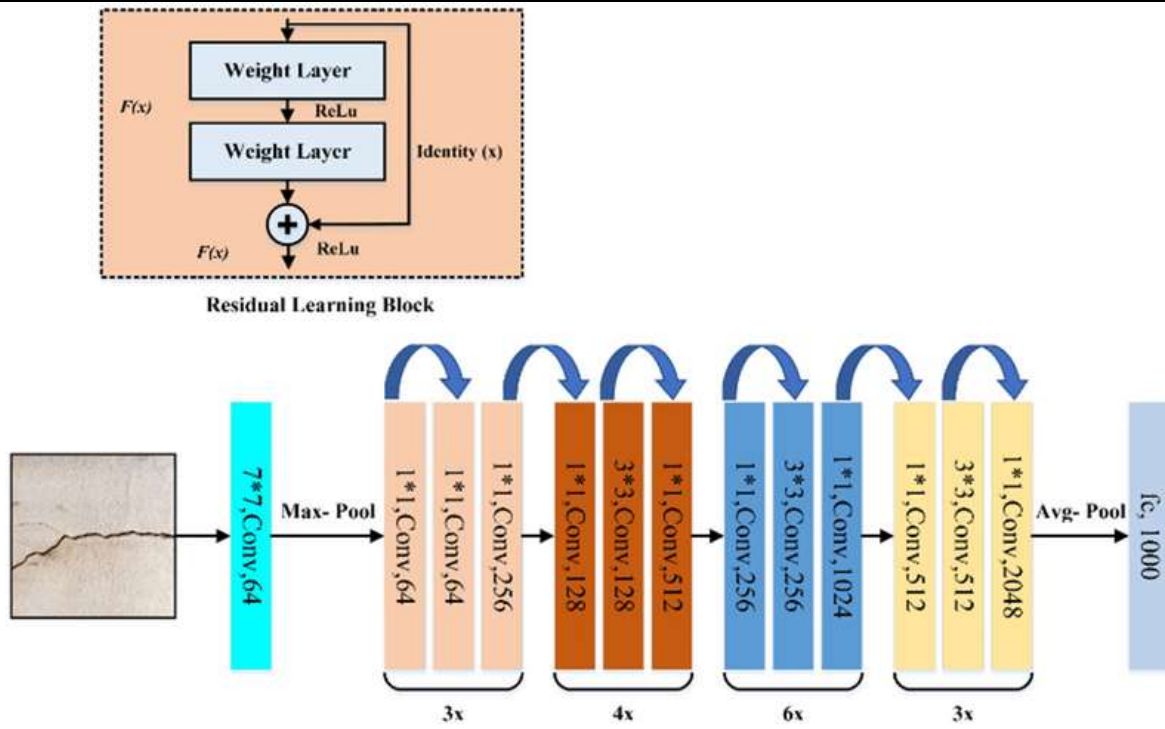


Figure 4-ResNet-50

4.Results and Screenshots

4.1Data collection:

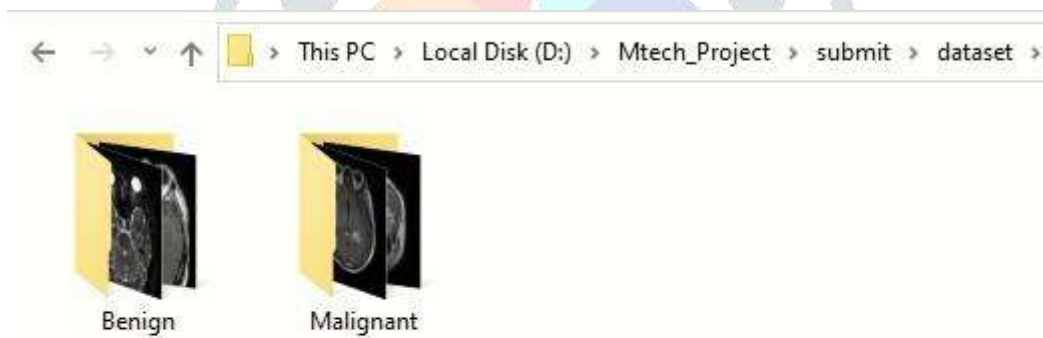


Fig 4 Dataset in local drive

Image Preprocessing:

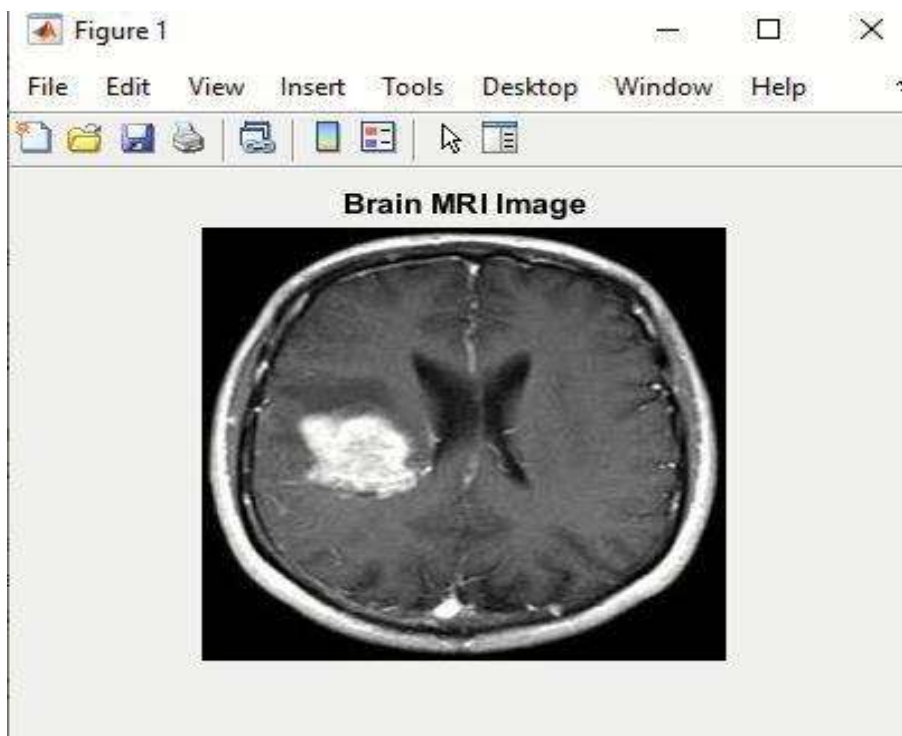


Fig 5 The inputted image

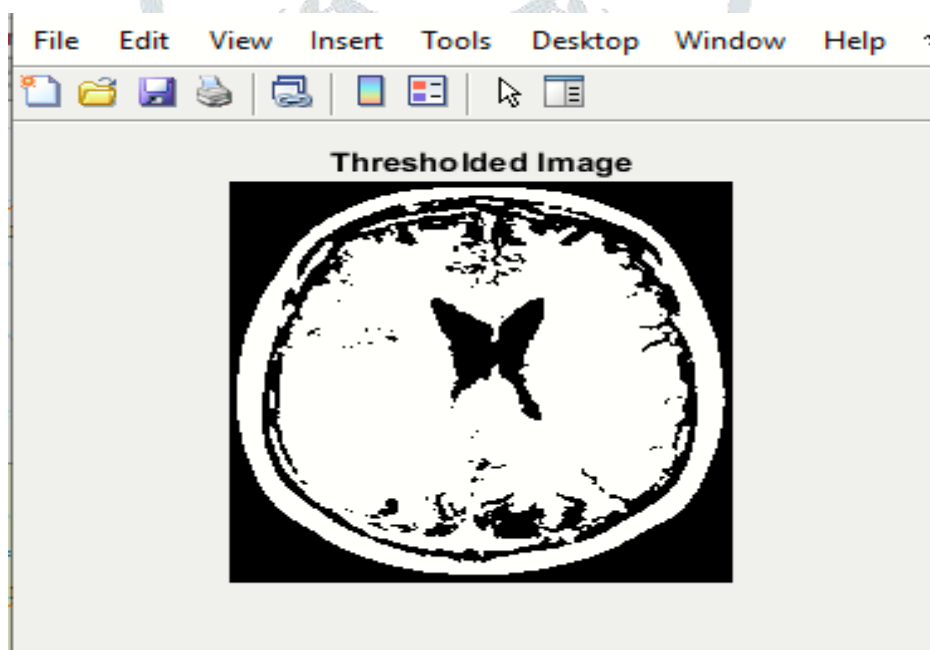


Fig6 Thresholded image

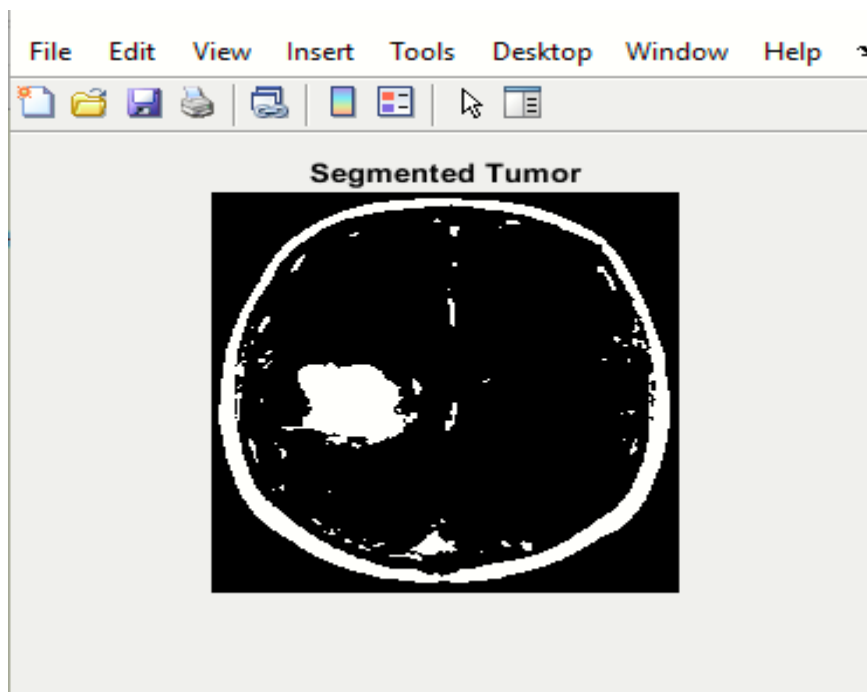


Fig 7 Segmentation

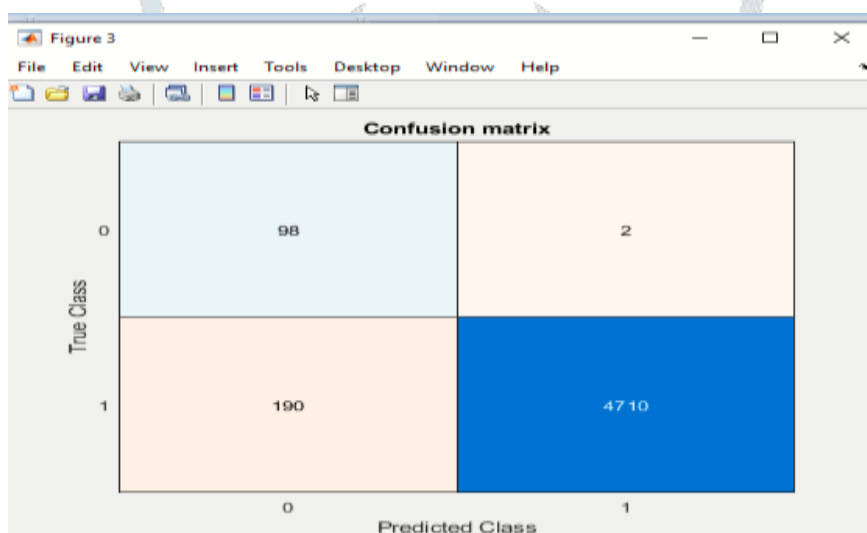


Fig 8 Confusion matrix for SVM

Results obtained in ResNet-50

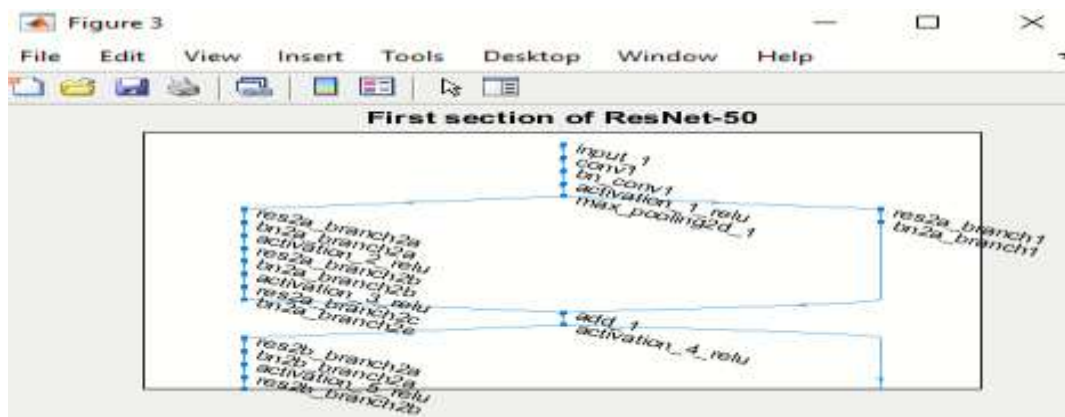


Fig 9 First section of CNN



Fig-10 Weights of first convolution layer

| | | | |
|------------|-----------|-----------------|-----------|
| True Class | Benign | 234 | 42 |
| | Malignant | 15 | 261 |
| | | Benign | Malignant |
| | | Predicted Class | |

Fig-11 confusion matrix

CONCLUSION AND FUTUREWORK

function normally. Identification of precise and significant information using algorithms with the least amount of error is the primary objective of medical image processing brain tumor

The detection and categorization using MRI images may be made sections: image collection, image segmentation, and feature extraction, image classification and by getting better outcomes, the system's effectiveness may be increased.

The region growing strategy produces better outcomes than the border approach and the edge-based approach in segmentation. It is discovered that the tumours are segregated most precisely.

Efficiency is improved by the features extracted using the GLCM approach since it allows for the extraction of fine tumour details utilizing a variety of characteristics. Convolution neural networks were shown experimentally to have the greatest classification accuracy of the many classification methods investigated. Since a patient's life depends on the outcomes the system predicts, accuracy and dependability are crucial in tumour diagnosis.

As comparison between SVM and CNN, it is found that for small amount of dataset SVM gives proper accuracy and CNN takes large number of dataset to do training and better classification.

The suggested technique aids in improving accuracy and providing the desired outcomes.

The future scope of this project will be categorizing the tumor not only as Benign or Malignant but also the different types of malignant tumors and to improving accuracy.

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