A

PROJECT REPORT

ON

Brain Tumor Detection

Submitted by

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For Partial Fulfilment of the Requirements for Bachelor of Technology in Information Technology

Guided by

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CERTIFICATE

This is to certify that the project work entitled **Brain Tumor Detection** has been successfully carried out by **19IT431- Sneh Shah, 19IT440- Akshay Kathiriya, 20IT606- Anchal Singh** for the subject **Project I (4IT31)** during the academic year 2022-23, Semester- VII for the partial fulfilment of Bachelor of Technology in Information Technology. The work carried out during the semester is satisfactory.

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We would like to express my gratitude to the HOD of IT Department **Dr. Keyur Brahmbhatt** and we are also grateful to all our **faculty members of BVM Engineering College**, IT Department for their kind cooperation and encouragement which helped me in completing this project and preparing the report.

Last but not the least, we would also like to thank my colleagues, who have co – operated during the preparation of my report and without them this project has not been possible. Their ideas helped me a lot to improve my project report.

ABSTRACT

As Brain tumor is one of the leading causes of death. A brain tumor is a growth of abnormal cells in the brain. Primary and secondary brain tumours are the two main categories. Primary brain tumours develop in the brain's tissues or tissues nearby. Secondary brain tumours are tumours that develop when cancer spreads from another part of the body to the brain. So, this project work concentrates on MRI images having brain tumor and classifies in benign and malign. Here, Discreate wavelet transform, Principal Component Analysis is used for feature extraction. Support Vector Machine and Convolutional Neural Network is used for classification. The results are tested on Kaggle dataset and achieved improved accuracy then other paper which have done work on different dataset.

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Chapter 1: Introduction

The central nervous system (CNS), which is made up of the brain and spinal column, regulates all essential bodily processes. These processes include voice, movement, and thought. This implies that a person's mental processes, speech, or movement might be affected when a tumour arises in the CNS. According to [15], about 24,000 people pass away each year as a result of brain tumours. The brain cancer market is predicted to develop at a compound annual growth rate of 1.11 percent through 2030, according to [14]. If the predictions come true, brain tumours may rank as the second most frequent malignancy by 2030, according to medical authorities.

The usual method to detect brain tumor is Magnetic Resonance Imaging (MRI) scans. Our proposed methodology will identify the tumor from MR image by using Machine Learning algorithm. Our system will identify tumor very fast in efficiently

1.1 Brief overview of the work

Brain tumor detection focuses on MRI images of brain tumors and classifies them as benign or malignant. For feature extraction, the discrete wavelet transform is used, and the support vector machine is used for classification. The Kaggle Dataset was used to test the results and improve the accuracy over other papers that worked on different datasets.

1.2 Objective

- To study Machine Learning and Deep Learning Algorithms which are useful in brain tumor detection
- To study Image pre-processing and feature extraction algorithms
- To achieve greater accuracy than existing models
- Pinpoint the major focus on the research.

1.3 Scope

Our Proposed model can easily classify MR image uploaded by the user in malignant or benign. The MR picture should be taken from upward of the brain. Model is trained on particular type of MR images which are taken from particular angle of the brain. Model can be used after image is taken in machine. Image should be clean and with less noise. Model does not provide live detection of tumor in MR scan.

1.4 Project Modules

1. **Data Collection**

   Data is gathered from a variety of sources, including Kaggle, GitHub, and Figshare. After analyzing the datasets, the Kaggle dataset is chosen for further investigation. The dataset includes 3000 MR images of the brain, with an equal distribution of malignant and benign tumors.

2. **Image Pre-processing**

   The images in the dataset are not all the same size. As a result, images are resized to a specific pixel size and RGB images are converted to grayscale images.

3. **Feature Extraction**

   It is very important part of any machine learning model. Various algorithms are used for the feature extraction in this project like Discrete Wavelet Transform, Principal Component Analysis and extraction through central tendency.

4. **Image Classification**

   For classification, the Support Vector Machine and CNN algorithms are used. SVM classification also employs linear, polynomial, and rbf kernels.

5. **Model Deployment**

   The streamlit library, which is based on Python, is used to create a simple and user-friendly UI. The user can upload an MR image of the brain and determine whether the tumor is malignant or benign.

1.5 Project Hardware/Software Requirements

1.5.1 Hardware requirement

- Operating system- Windows 7,8,10,11
- Processor- Quad core 2.4 GHz (i5 or i7 series Intel processor or equivalent AMD)
- RAM-8 GB

1.5.2 Software requirement

- Python
- Jupyter Notebook / PyCharm
- Numpy
- Pandas
- Seaborn / Matplotlib
- Sklearn
- TensorFlow & Keras
- Opencv
- Streamlit

Chapter 2: Literature Review

Machine Learning and Deep Learning Techniques are widely used in different medical domains. Viewed research papers proposed various techniques and conclude its result.

To reduce the computation, it is necessary to reduce data. Also features should not be reduced. Central moments i.e., mean and standard deviation are used to extract features from images used in [1]. Proposed methodology has achieved maximum 91.91% accuracy using Artificial Neural Network. They have resized the image in 128x128 pixels. Then each image is separated in 16x16 pixels size windows. Mean, Variance and Standard Deviation is extracted from each window and constructed new array. This array is representing central moments of each window of image. By applying this technique size of the image is reduced from 128x128 to 8x8. So it is easy to implement classification algorithm. Four types of approaches have been applied to classify the images. Image size of 256x256 pixels is used in our methodology for better information and results.

Feature extraction is necessary before applying classification algorithm. Wavelet transforms are mathematical tools for analyzing data where features vary over different scales. For signals, features can be frequencies varying over time, transients, or slowly varying trends. For images, features include edges and textures. Wavelet Transform provides loss less data reduction and extract important features. Discrete wavelet Transform (DWT) is used by [12]. DWT has applied to 1000 images to classify leaf images into three categories. They have used this technique for feature extraction from leaf images.

Principal Component Analysis (PCA) is also useful in feature extraction and dimension reduction, but it is lossy reduction. [13] have used PCA for feature extraction on cancer images. They have classified three different types of cancer based on three types of features. Using PCA they have achieved 98,98 and 96 percent accuracy respectively for each feature with Naïve Bayes and 97,98 and 97 percent accuracy with support vector machine.

Deep Learning is used to solve more complex problems. Convolutional Neural Network (CNN) is more useful when we have data in terms of images. CNN can extract features by itself, we don't have to apply any specific algorithm for that. Waleed Saad. Et al. has introduced classification using CNN algorithm [4]. The CNN model used is with 8 convolutional layers. Also max normalization is applied after every convolutional layer. SoftMax activation function

used in output layer that classify the image into malignant or benign tumor. They have trained the model using various learning rate. Train test splitting ratio of 70:30 and 80:20 used to train the model. They have achieved 94.14% and 96.05% accuracy on train-test split ratio 70:30 and 80:20 respectively with the learning rate of 0.0001.

Deep Learning is used to solve more complex problems. Artificial Neural Network (ANN) algorithm is simple interconnected network of neurons. ANN and CNN are used in [5]. P Gokila Brindha, M Kavinraj, P Manivasakam and P Prasanth have used ANN and CNN for tumor detection. Dataset is downloaded from GitHub. Model is trained on 2065 images in which 1085 images are tumorous and 980 images are not tumorous. CNN is constructed with five convolution layers with max pooling. Adam is used to optimize the result of the CNN model. Accuracy achieved by ANN is 71.51% and CNN is 94%. ANN is not able to extract features from images therefor any feature extraction algorithm should be applied before feeding data in ANN. By applying feature extraction method ANN accuracy could have been increased.

GoogLeNet is convolutional neural network that has 22 layers deep and ResNet-18 is convolutional neural network with 18 layers. These algorithms are specially used for object detection in images, used in [2]. S. Arora and M. Sharma has proposed ResNet, GoogleNet, ResNet-18 with SVM and GoogleNet with SVM algorithms with accuracy of 97.8%, 97.4%, 98% and 97.6% respectively. They have used data augmentation to increase size of the dataset. By rotating the image 45º four times, size of dataset is increased to 15320 images from 3064 images. Transfer learning is also used to increase accuracy of the model. Authors have achieved more accuracy using these algorithms than models they have studied.

Naïve Bayes and Decision trees are also used for classification. J48 is classifier that is used to generate decision tree. These techniques are used in [8]. Al-Ayyoub, Mahmoud, et al. proposed algorithms like Artificial Neural Network, J48, Naïve Bayes and Lazy-IBK. Accuracy achieved is 66.6%, 59.2%, 59.2%, 62.9% respectively. Some algorithms are directly applied from the weka tool. Any feature extraction algorithm is not applied on the dataset. As machine learning algorithm can not extract features from given data. It can affect the accuracy of the model.

Chapter 3: System Analysis & Design

3.1 Project Feasibility Study

3.1.1 Technical Feasibility:

- This system will be implemented using latest versions of VS code, python, YOLO v3, Git Hub, NumPy, Microsoft Word.
- All these above Applications are technically feasible.

3.1.2 Operational Feasibility:

- Service is flexible and expandable.
- Easy to use and implement
- It makes maximum use of available resources, including people, time, and flow of forms.
- Provides Reliable services
- Highly accurate system

3.1.3 Implementation Feasibility:

- friendly UI has been implemented so anyone can directly access the system
- User can upload MR image and get the result
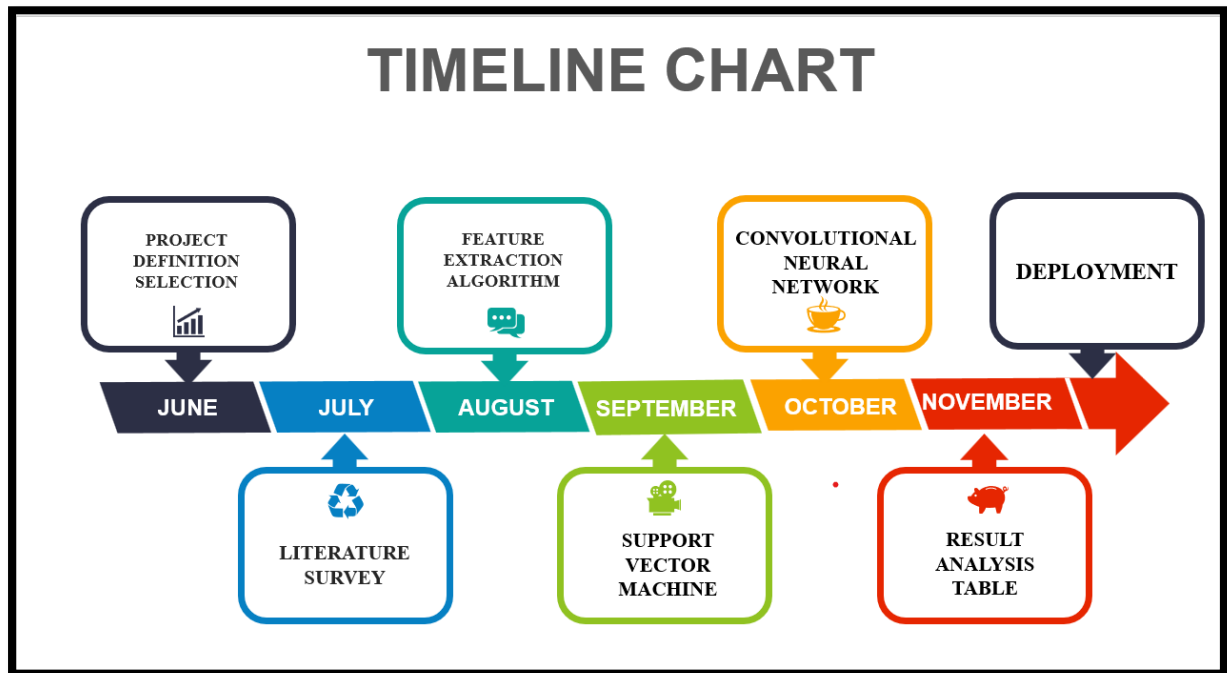
3.2 Project Timeline Chart

Figure 1: Timeline chart

3.3 Detailed Modules Description

3.3.1 Data Collection:

Data is collected from various sources. The dataset survey is shown in below table

Sr No	Dataset	Survey
1	Kaggle	• 3000 Images • Labelled Images
2	Figshare	• 766 Images • In the form of Access Database
3	Github	• 4-Class Classification • 2870 Training Images • Mixed type of images • Probably hard to achieve high accuracy
4	Github	• 253 Images

		• Labelled images

Table 1 Data Collection

After studying various dataset, we have decided to work on the Kaggle dataset. It has 3000 labelled images distributed equally in malignant and benign classes.

3.3.2 Image Pre-processing

Data Pre-processing is most essential step for any ML or DL model. It directly affects the accuracy of the model. So clean and suitable data for the model is needed.

Dataset images size is not fixed. To feed the image as input to model, we have to normalize the size of the image in terms of the pixels. So as per the various methods we have resized the images to 64 x 64 for DWT and PCA, 128 x 128 for CNN and 256 x 256 for central tendency method.

Also, the images pixels are in 3-dimensions as RGB so, converted the image in grey scale. This process converted image into 2-dimension from 3-dimension. This would reduce computation time and training time of the model.
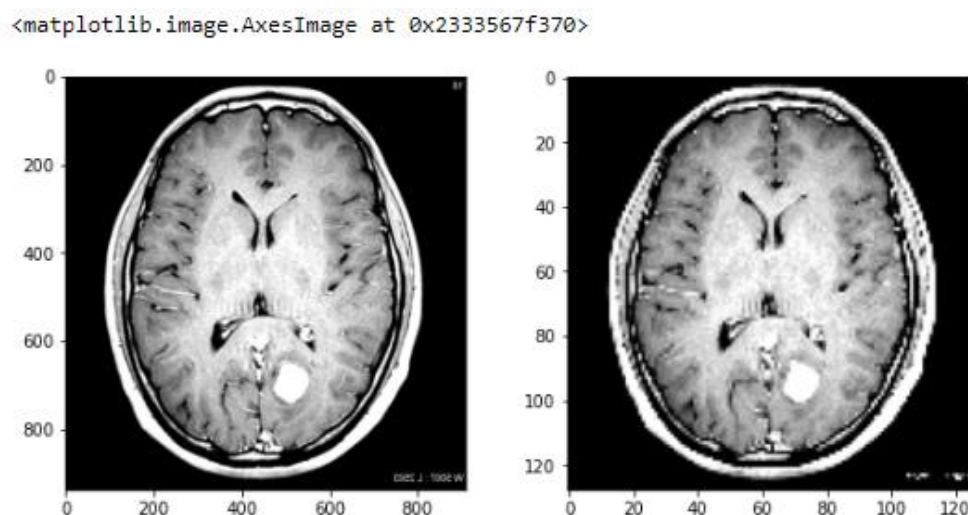

Figure 2: Image Conversion from RGB to Grey Scale.

3.3.3 Feature Extraction

Feature extraction helps to reduce the amount of redundant data from the data set. In the

end, the reduction of the data helps to build the model with less machine effort and also increases the speed of learning and generalization steps in the machine learning process.

Feature Extraction Algorithm have been implemented.

3.3.3.1 Discrete Wavelet Transform (DWT)

Wavelet Transform is widely used for feature extraction in Machine Learning. In this research paper Discrete Wavelet Transform is used for feature extraction.

DWT on any image, image will decompose in two parts i) Low pass Decomposition filter and ii) High pass Decomposition filter. Then again both decomposed in two-two parts. After second decomposition we get four coefficients i) Approximation Coef. ii) Horizontal Detailed Coef. iii) Vertical Detailed Coef. iv) Diagonal Detailed Coef.
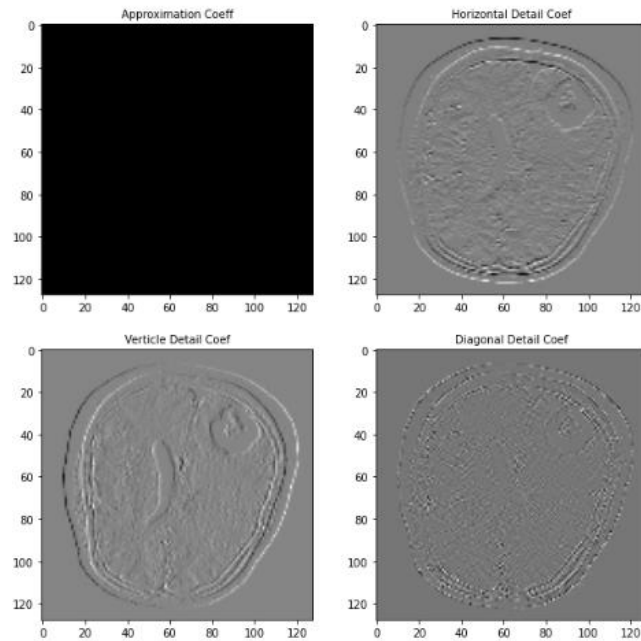

Figure 3 : Image with four coefficients after decomposition

After obtaining four coefficients, the Approximation Coef. is further decomposed into four parts, which is known as level two decompositions. This paper used a 6-level decomposition. In this operation, the study reduced some coefficient parts to zero in order to obtain better results.

(a) First level of decomposition

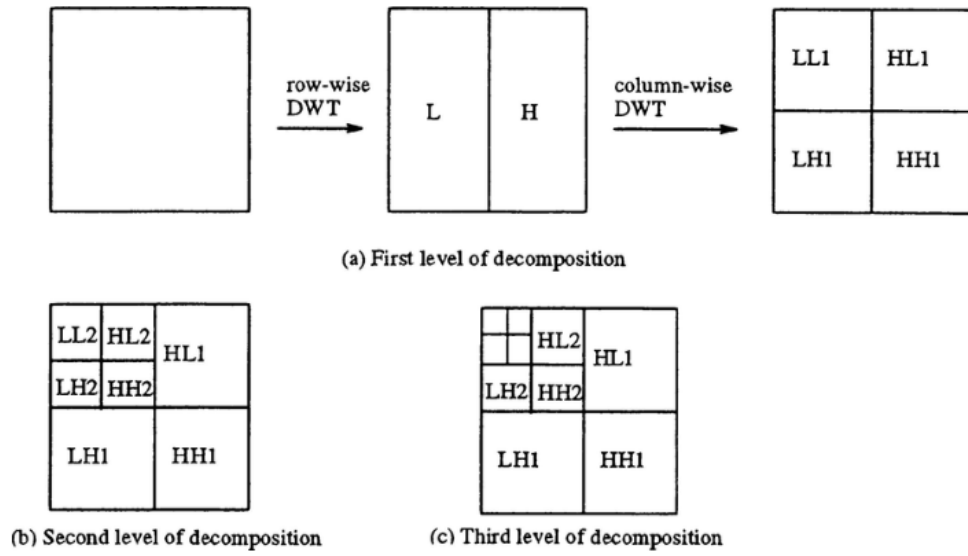(b) Second level of decomposition   (c) Third level of decomposition

Figure 4 : Different level of decomposition [16]

This paper recomposed the image after performing decomposition. The comparison of both images before and after applying the DWT is shown below.
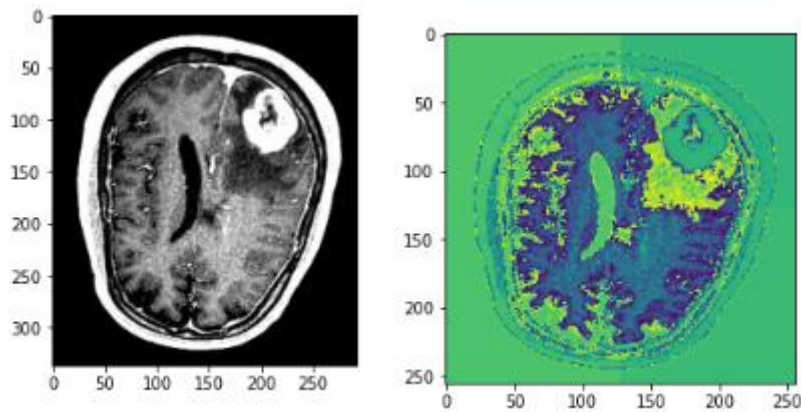

Figure 5 : Images Before and After applying the DWT

3.3.3.2 Principal Component Analysis (PCA):

Principal Component Analysis (PCA) is a linear dimensionality reduction technique (algorithm) that transform a set of correlated variables (p) into a smaller k (k<p) number of uncorrelated variables called principal components while keeping as much of the variability in the original data as possible.
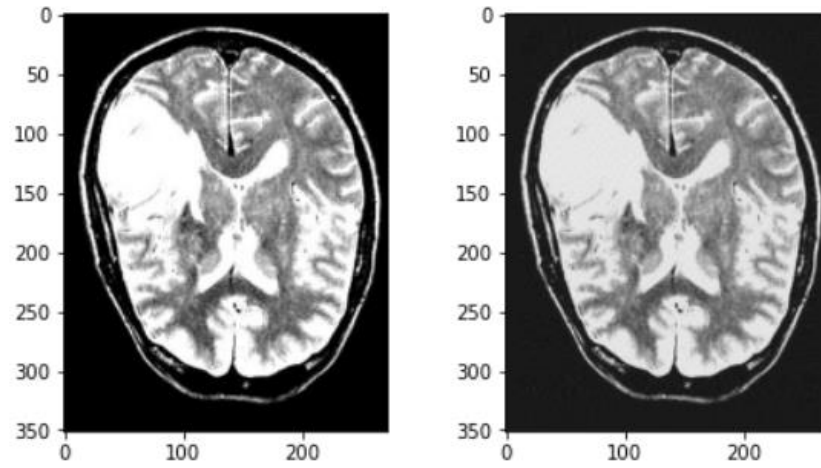
Input and Output Image:

Figure 6 : Input/Output Image in PCA

Below images are output of given input image by applying various dimensions.
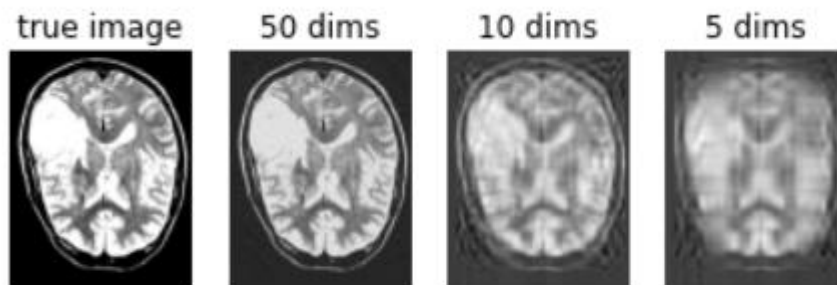

Figure 7 : Image after applying various dimensions in PCA.

Image quality decreases as the number of dimensions or components increases. This research paper always strives to maintain an optimal number of components that balance explained variability and image quality.

As a result, study kept the dimensions same.

3.3.3.3 Central Moments

Now, we obtain our features by calculating and storing the central moments window in this paper. The pivotal moments are

$$\mu = \frac{\sum_{i=1}^{N} I(p(i))}{N}$$

(3.1)

$$\sigma^2 = \frac{\sum_{i=1}^{N}(I(p(i)) - \mu)^2}{N}$$

(3.2)

$$\sigma = \sqrt{\left\{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(xi - \mu)^2\right\}}$$

(3.3)

In this method we have taken the image size of 256 x 256 and segment it into 16 x 16 window. Central moments of each window stored in the metrics. This method helps to reduce the data significantly and make the training faster.

3.3.4 Classification

To classify tumor malignant or benign This paper has implemented Support Vector Machine (SVM) and Convolutional Neural Network (CNN).

3.3.4.1 Support Vector Machine (SVM):

One of the most widely used classification techniques is the Support Vector Machine. To separate n-dimensional datasets, SVM generates the best line or hyperplane. SVM chooses the most extreme points to establish the hyperplane. Support vectors are points that are used to calculate maximum distance or maximum margin.
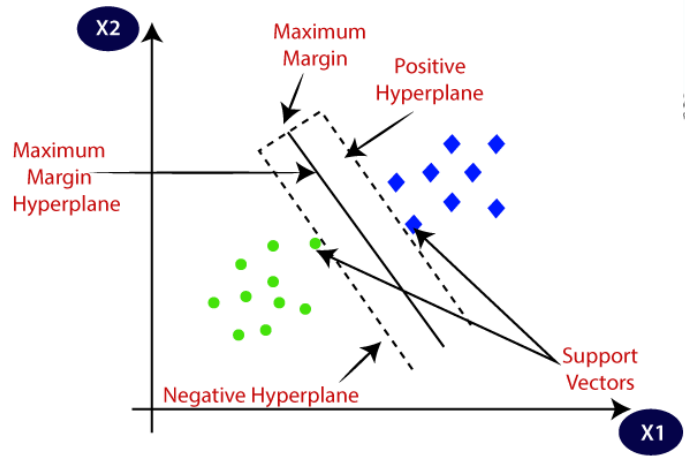
Figure 8 : Support Vector Machine [17]

This paper used various kernels in SVM to fit best hyperplane and achieve more accuracy. In this research paper we have used three different kernels:

1. Linear kernel uses single line to separate the data points
2. When the data is not linearly separable polynomial curve is used for classification
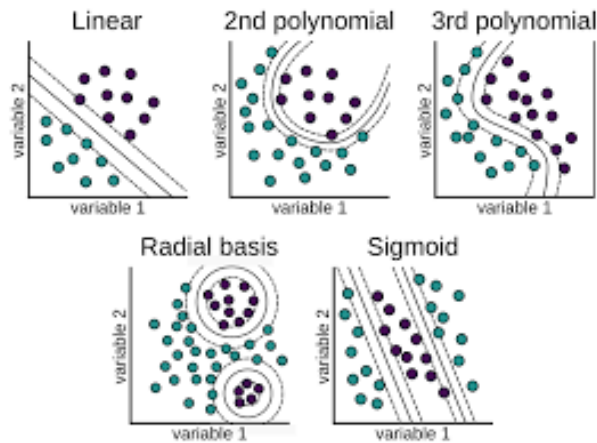3. When the data is linearly inseparable RBF kernel is recommended

Figure 9: Kernels of SVM [18]

3.3.4.2 Convolutional Neural Network (CNN)

Convolutional Neural Networks (ConvNets or CNNs) are a category of Neural Networks that have proven very effective in areas such as image recognition and classification. ConvNets have been successful in identifying faces, objects and traffic

signs apart from powering vision in robots and self-driving cars.

There are four main operations in the ConvNet shown in Figure 3 above:

1.   Convolution
2.   Non Linearity (ReLU)
3.   Pooling or Sub Sampling
4.   Classification (Fully Connected Layer)

The Convolution Step:

ConvNets derive their name from the "convolution" operator. The primary purpose of Convolution in case of a ConvNet is to extract features from the input image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input data. We will not go into the mathematical details of Convolution here, but will try to understand how it works over images.

As this paper discussed above, every image can be considered as a matrix of pixel values. Consider a 5 x 5 image whose pixel values are only 0 and 1 (note that for a grayscale image, pixel values range from 0 to 255, the green matrix below is a special case where pixel values are only 0 and 1):

Also, consider another 3 x 3 matrix as shown below:

Then, the Convolution of the 5 x 5 image and the 3 x 3 matrix can be computed as shown in the animation in Figure 5 below:
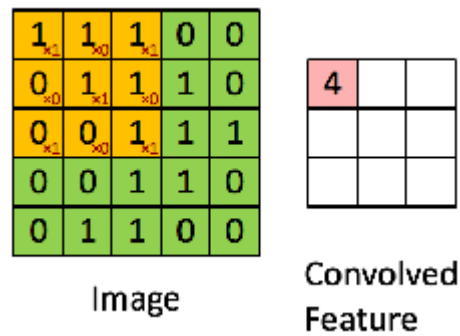
Image   Convolved Feature

Figure 10 : The Convolution operation. The output matrix is called Convolved Feature or Feature Map.

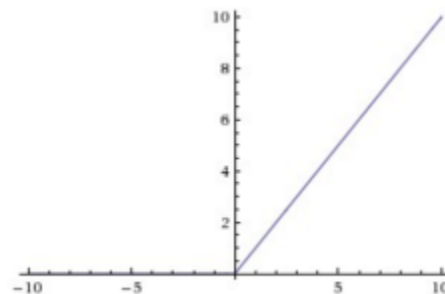Non-Linearity (ReLU)

$$Output = Max(zero, Input)$$

Figure 10 : ReLU [19]

ReLU is an element-wise (pixel-by-pixel) operation that replaces all negative pixel values in the feature map with zero. The goal of ReLU is to introduce non-linearity into our ConvNet, because the majority of the real-world data this paper want in ConvNet to learn is non-linear (Convolution is a linear operation – element wise matrix multiplication and addition, so we account for non-linearity by introducing a non-linear function like ReLU).

The Pooling Step

Spatial Pooling (also called subsampling or down sampling) reduces the dimensionality of each feature map but retains the most important information. Spatial Pooling can be of different types: Max, Average, Sum etc.
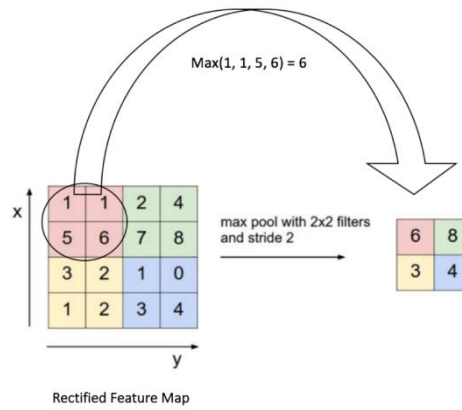
15

Figure 11 : Max Pooling [20]

Fully Connected Layer

The Fully Connected layer is a traditional Multi Layer Perceptron that uses a softmax activation function in the output layer (other classifiers like SVM can also be used, but will stick to softmax in this post). The term "Fully Connected" implies that every neuron in the previous layer is connected to every neuron on the next layer.
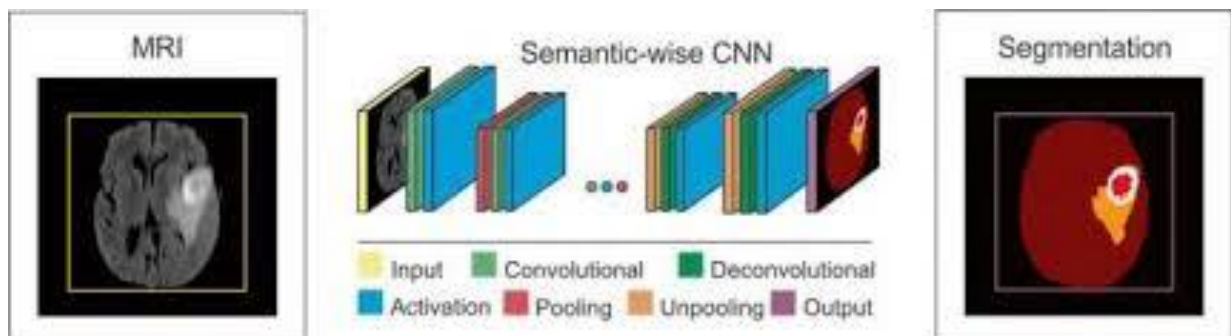

Figure 12 : CNN model [21]

Layers of CNN model used in this model:

1. Convolution 2D

In the Convolution 2D extract the featured from input image. It given the output in matrix form.

2. Max Pooling 2D

In the MAX polling 2D it takes the largest element from rectified feature map.

3. Dropout

Dropout is randomly selected neurons are ignored during training.

4. Flatten

Flatten feed output into fully connected layer. It gives data in list form.

5. Dense

A Linear operation in which every input is connected to every output by weight. It followed by nonlinear activation function.

6. Activation

It used Sigmoid function and predict the probability 0 and 1.

3.4 Project SRS
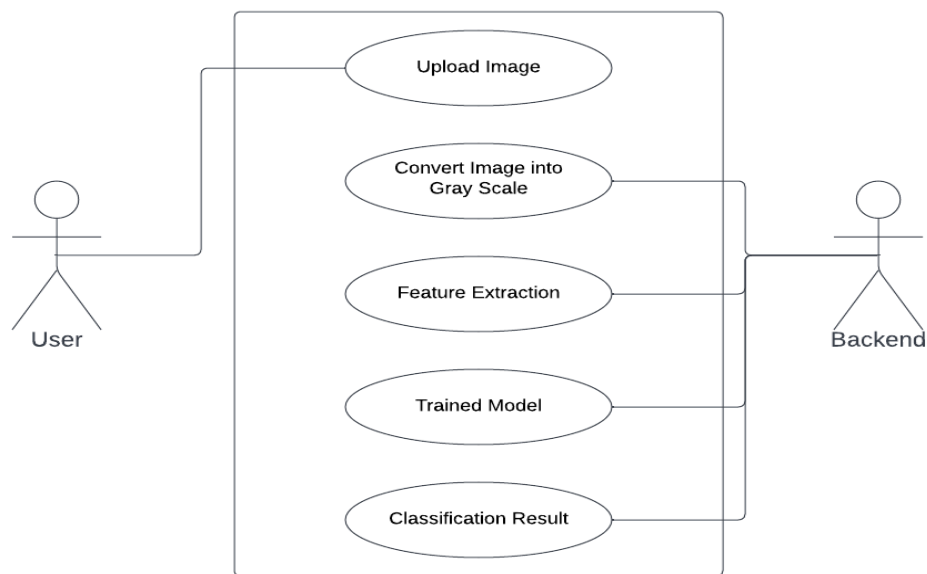
3.4.1 Use Case Diagram

Figure 13 : Use Case Diagram

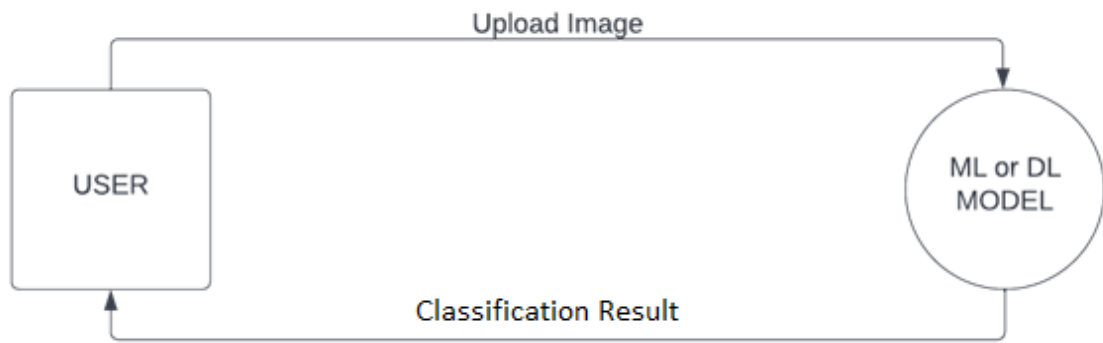### 3.4.2 Data Flow Diagram

- **Level 0**

Figure 14 : Data Flow Diagram: Level 0
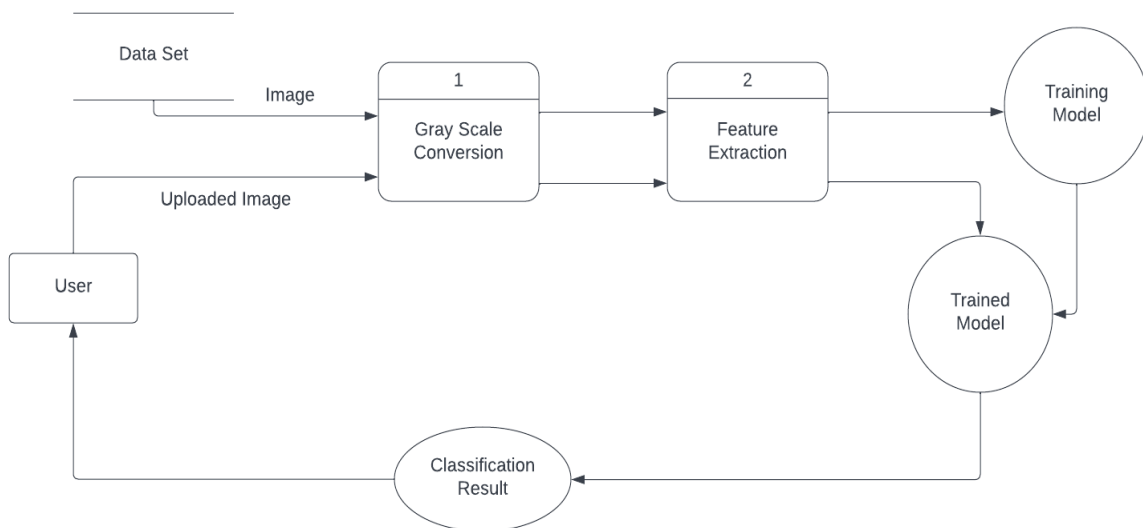
- **Level 1**

Figure 15 : Data Flow Diagram: Level 1
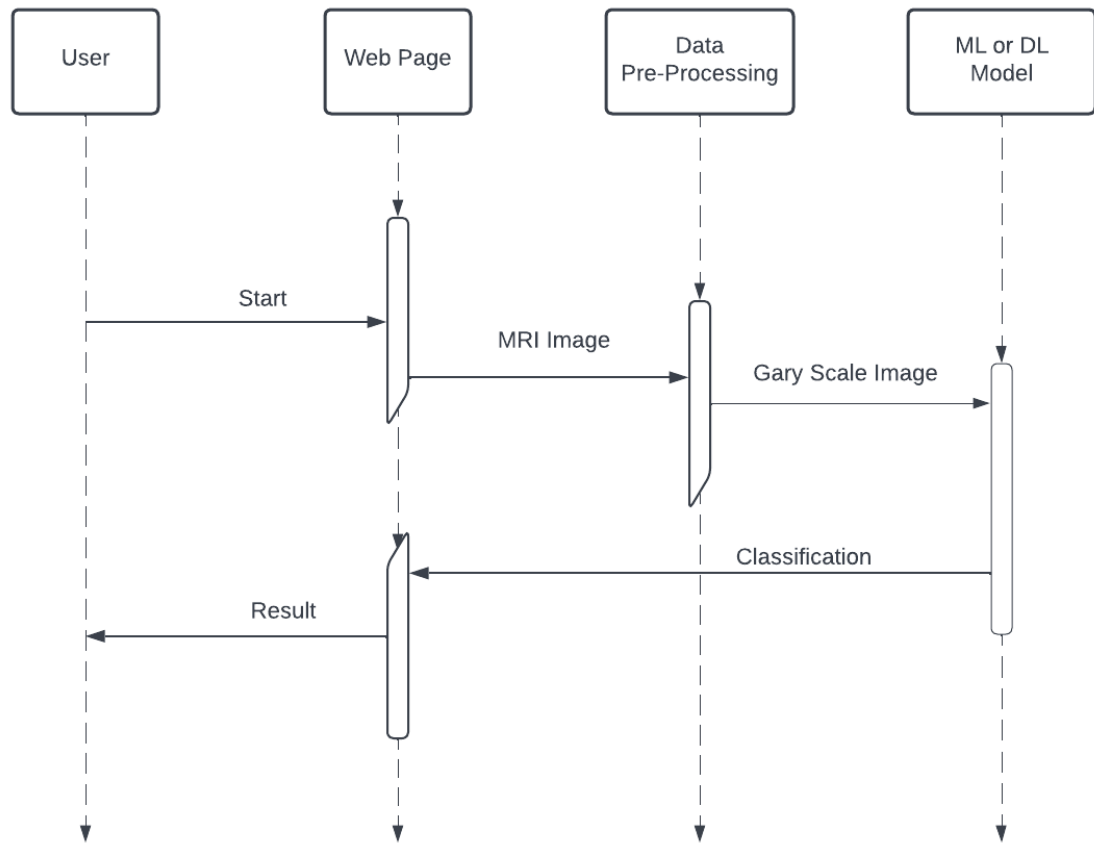
3.4.3 Sequence Diagram:

Figure 16 : Sequence Diagram

Chapter 4: Implementation and Testing

4.1 User Interface and Snapshot

User Interface is a point of human computer interaction and communication in a device. UI should be simple and user friendly. User should not face any problem using UI.

This paper created a simple UI in Python using the Streamlit library. The user can upload an MR image of the brain to determine whether the tumour is malignant or benign. The user can also choose from a variety of ML and DL models that we have trained. The user can also view the performance of each model using a bar chart. This paper had created an accuracy table for each model that is trained.

Streamlit is an open-source Python library that makes it easy to create and share beautiful, custom web apps for machine learning and data science. In just a few minutes you can build and deploy powerful data apps.

To install streamlit on your pc you have to run below command in the terminal

<div align="center">pip install streamlit</div>

Streamlit provides easy APIs for different widgets of the webpage. We can code front end and back end both in one file. We don't have to maintain numbers of file for front and back end.
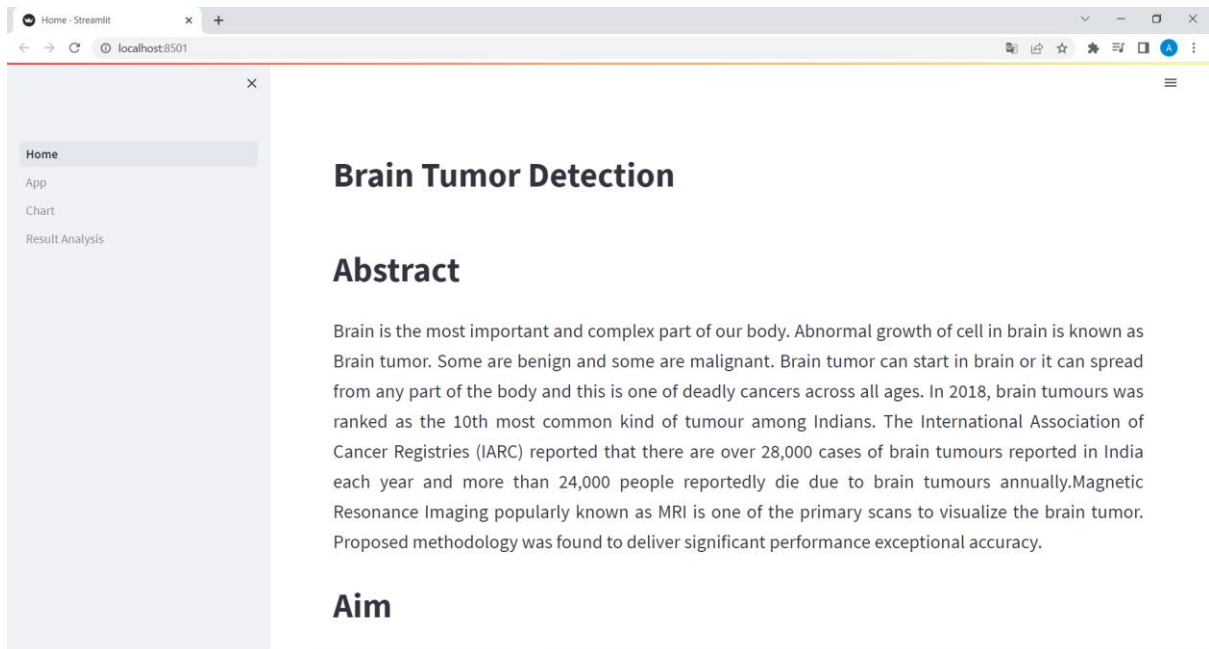
Home page of web app

Figure 17 : Home Page

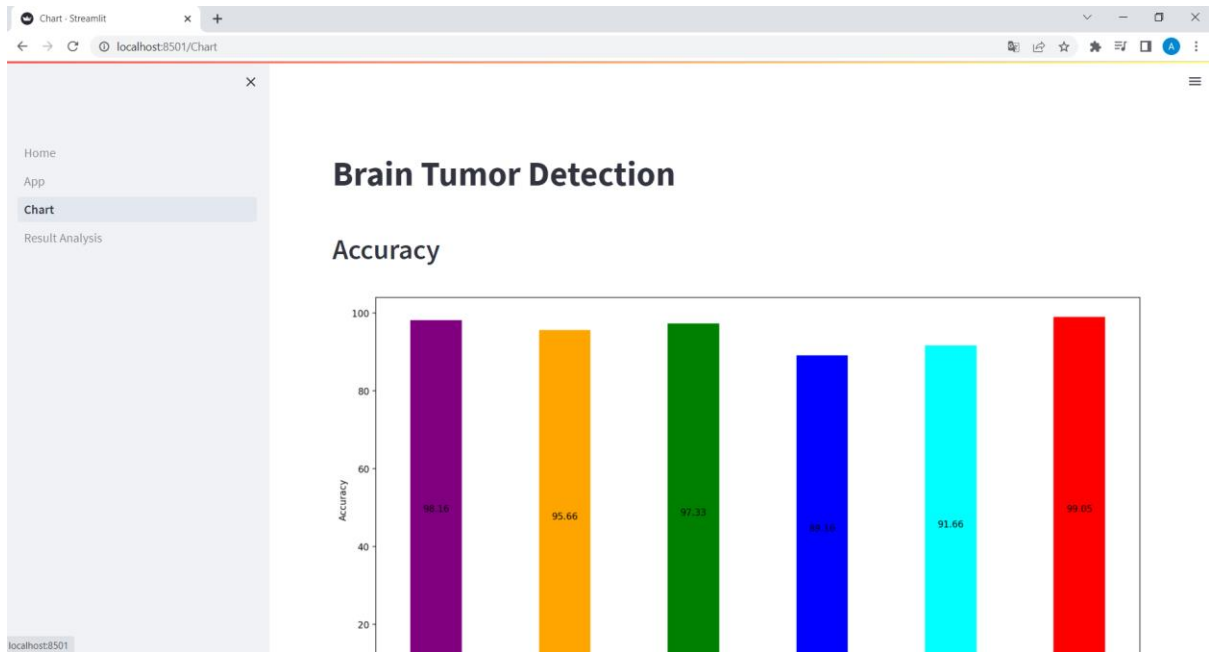This page contains Accuracy, Precision, Recall Chart for analysis purpose.

Figure 18 : Bar-Chart Page

Page showing different Model which can be choose from dropdown menu.
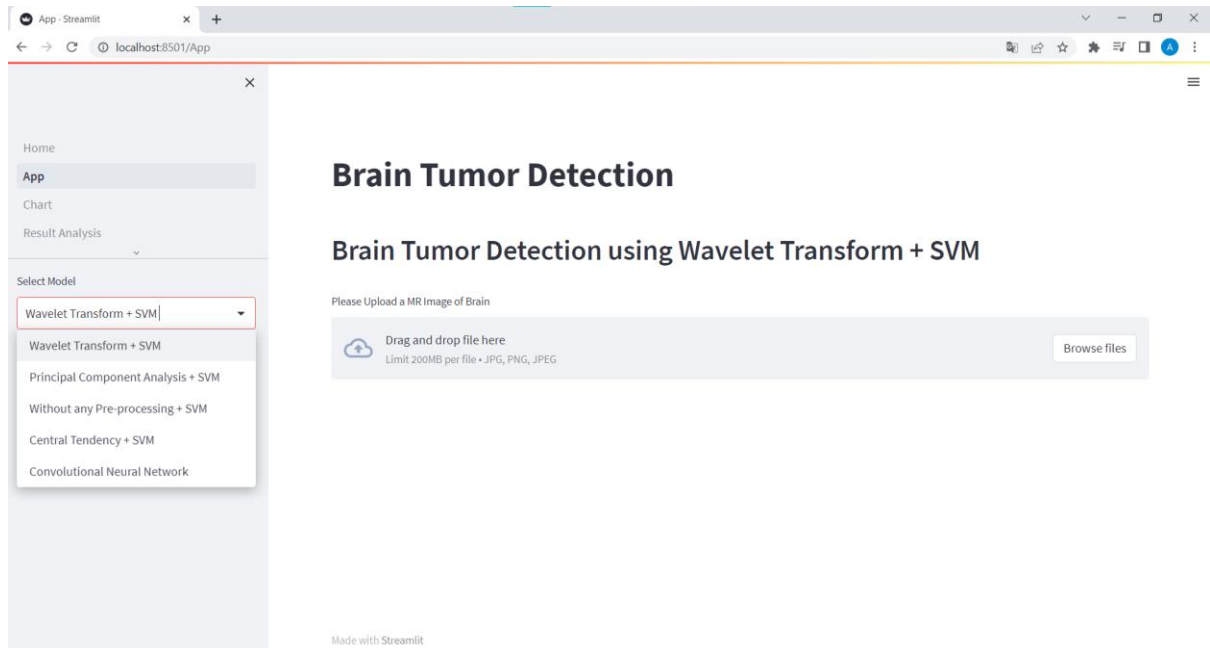

Figure 19 : Main App Page

4.2 Testing using Use Cases

Browsing MRImage from local system.
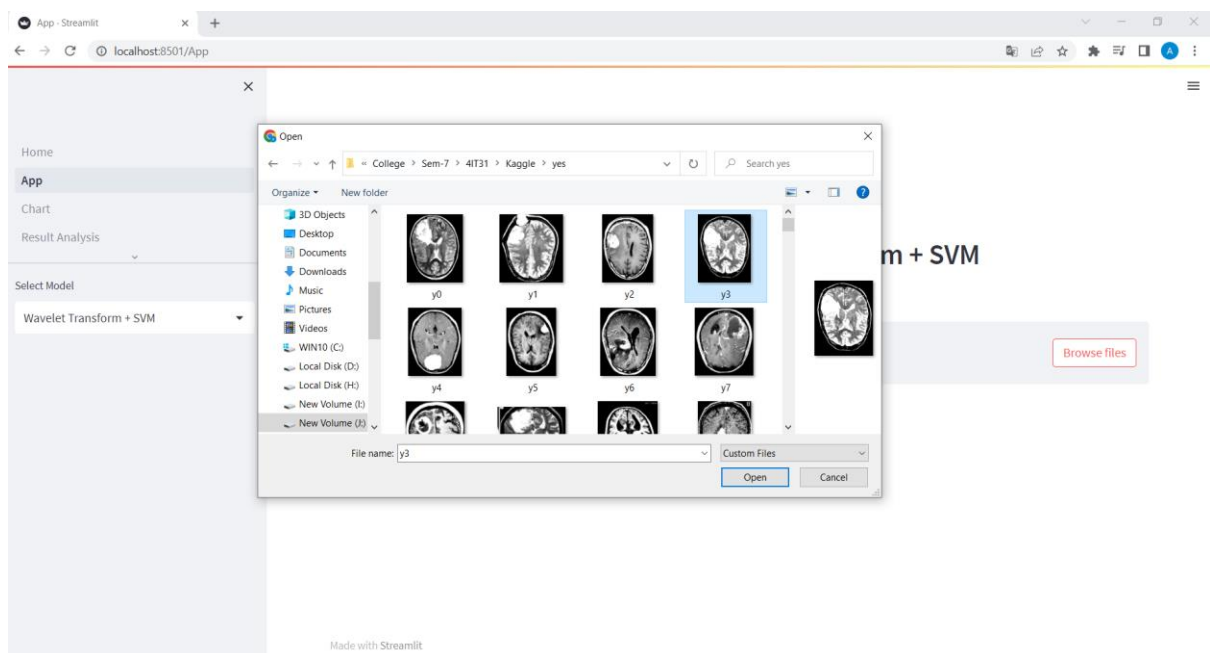
Figure 20 : Selecting MRImage

By Selecting Wavelet Transform and SVM model for classify MRImage.
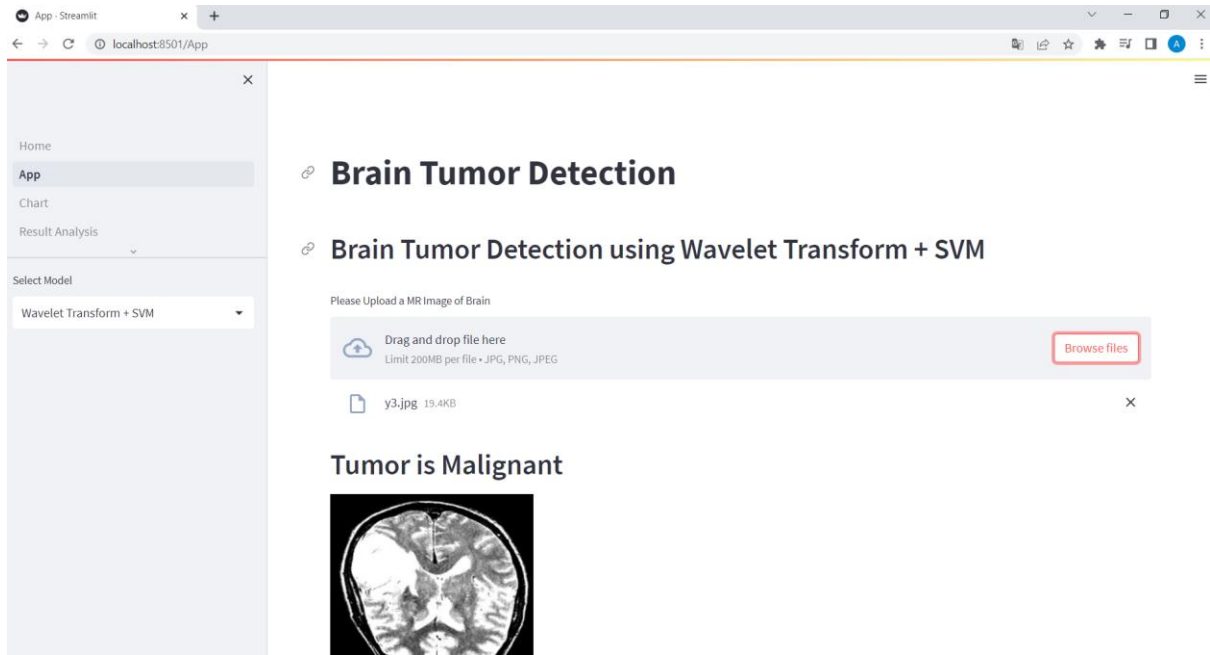
Figure 21 : Classified Image using Wavelet Transform and SVM

Page Classifying Image without any Pre-processing and SVM.

Figure 22 : Classified Image using Without Pre-processing and SVM

Model Classified Image as Benign.

Figure 23 : Classified Image as Benign

Result Analysis Page contains various analysis using different model with splitting Ratio 70:30 and 80:20.

Figure 24 : Result Analysis Page

4.3 Result Analysis

4.3.1 Splitting Ratio 70:30

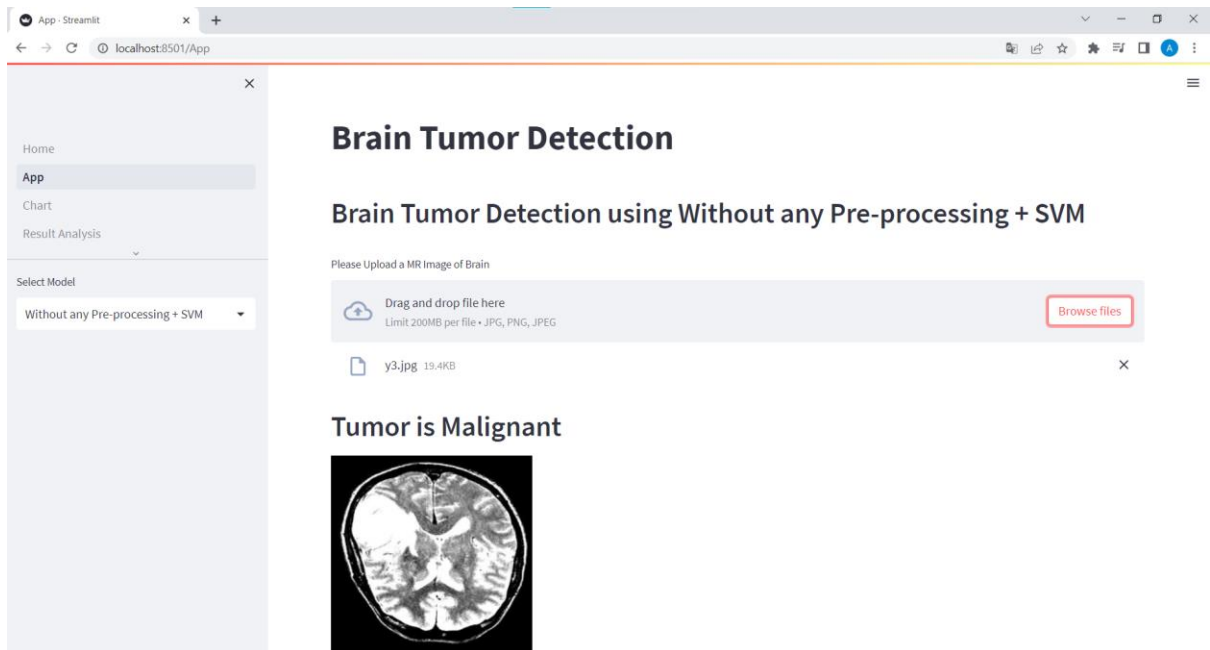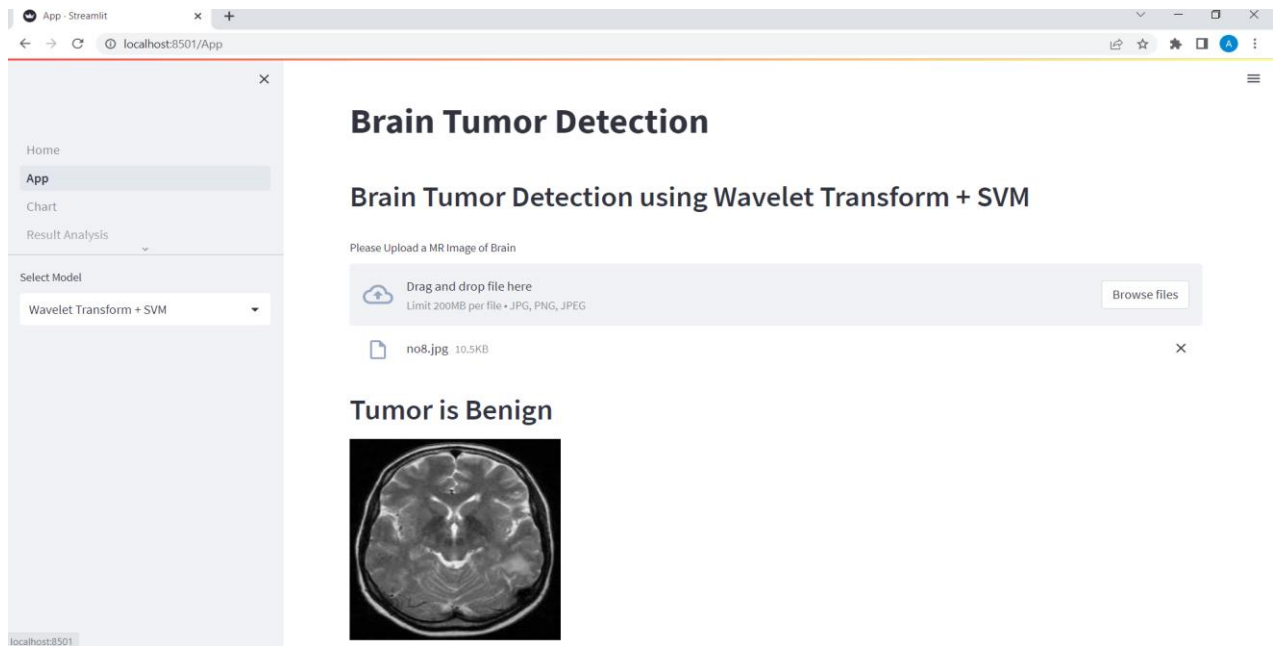| Model	Kernel	Accuracy	Precision	Recall
DWT + SVM	Linear	95.55%	95.97%	96.34%
	Polynomial	96.88	97.54	96.75%
	RBF	96.44	96.19	97.36
Without feature extraction + SVM	Linear	93.88	95.32	92.57
	Polynomial	92.11	96.11	88.23
	RBF	95.44	96.45	94.52
PCA + SVM	Linear	94.22	97.01	91.54
	Polynomial	92.66	96.25	89.15
	RBF	96.88	97.37	96.52
Central Tendency + SVM (128x128)	Linear	79.44	82.21	79.71
	Polynomial	82.88	94.25	73.22
	RBF	85.11	87.31	85.19
Central Tendency + SVM (256x256)	Linear	88.33	90.75	87.62
	Polynomial	89.88	96.31	84.87
	RBF	87.55	90.96	85.80
CNN	-	98.13	97.33	98.2

Table 2 : Result Analysis with 70:30 ratio

4.3.2 Splitting Ratio 80:20

Model	Kernel	Accuracy	Precision	Recall
DWT + SVM	Linear	96.5%	96.8%	97.08%
	Polynomial	98.16	98.53	98.25%
	RBF	97.33	97.11	98.25
Without feature extraction + SVM	Linear	94.66	95.75	93.91
	Polynomial	94.33	96.36	92.65
	RBF	95.66	96.10	95.48
PCA + SVM	Linear	95.33	97.07	94.02
	Polynomial	94.33	96.71	92.45
	RBF	97.33	97.40	97.84
Central Tendency + SVM(128x128)	Linear	80.5	85.31	79.59
	Polynomial	89.16	95.72	84.83
	RBF	87.5	89.64	88.33
Central Tendency + SVM(256x256)	Linear	89.66	93.76	87.75
	Polynomial	91.66	97.41	87.75
	RBF	89.16	91.61	89.21
CNN	-	99.05	98.33	99.1

Table 3 : Result Analysis with 80:20 ratio

Chapter 5: Conclusion & Future work

5.1 Conclusion

The proposed methodology outperforms other methodologies under consideration. The accuracy of feature extraction using Discrete Wavelet Transform and classification using SVM is higher than that of the studied model. Because PCA and central tendency are lossy data reduction techniques, they do not provide the expected accuracy. This paper achieved more than 99% accuracy using CNN, which is better than the models studied for this research.

5.2 Future Work

`ResNets were learned with network depth of as large as 152. It achieves better accuracy than VGGNet. Using ResNet has significantly enhanced the performance of neural networks with more layers and here is the plot of error% when comparing it with neural networks with plain layers. Clearly, the difference is huge in the networks with 34 layers where ResNet-34 has much lower error% as compared to plain-34.

GoogLeNet is a convolutional neural network that is 22 layers deep. You can load a pretrained version of the network trained on either the ImageNet or Places365 data sets. The network trained on ImageNet classifies images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. This network was responsible for setting a new state-of-the-art for classification and detection in the ILSVRC. This first version of the Inception network is referred to as GoogleNet.

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