

1. INTRODUCTION

1.1 Literature review

In Medical diagnosis, robustness and accuracy of the prediction algorithms are important, because the result is crucial for treatment of patients. There are many popular classification and clustering algorithms used for prediction. The goal of clustering a medical image is to simplify the representation of an image into a meaningful image and make it easier to analyse. Several Clustering and Classification algorithms are aimed at enhancing the prediction accuracy of diagnosis process in detecting abnormalities.

The first section of this chapter presents different pre-processing techniques on the MRI Images obtained. Types of Segmentation algorithms used are given in the second section. The next section discusses about the different feature extraction methods and finally the classification algorithms have been presented followed by the summary of this chapter.

1.1.1 Pre – Processing and Enhancement

Preprocessing and enhancement techniques are used to improve the detection of the suspicious region from Magnetic Resonance Image (MRI). This section presents the gradient-based image enhancement method for brain MR images, which is based on the first derivative and local statistics. The preprocessing and enhancement method consists of two steps: first, the removal of film artifacts such as labels and X-ray marks from the MRI using a tracking algorithm. Second, the removal of high-frequency components using anisotropic diffusion technique [2]. It gives high-resolution MRI compared to median filter, adaptive filter, and spatial filter. The performance of the proposed method is also evaluated by means of peak signal-to-noise ratio (PSNR) and average signal-to-noise ratio (ASNR).

1.1.2 Segmentation

Image segmentation is the primary step and the most critical tasks of image analysis. Its purpose is that of extracting from an image by means of image segmentation. The mechanization of medical image segmentation has established wide application in diverse areas such as verdict

for patients, treatment management planning, and computer - integrated surgery. Following are the segmentation algorithms that have been implemented:

1.1.3 Canny Algorithm:

Edge detection is the approach used most frequently for segmenting images based on abrupt change in intensity. The canny edge operator works in a multistage process. Canny algorithm was the only procedure capable of yielding a unbroken edge for the posterior boundary of the brain [5].

1.1.4 Otsu Thresholding:

Otsu's thresholding is a non - linear operation that converts a grayscale image into a binary image where the two levels are assigned to pixel those that are below or above the specified threshold value [4]. The two levels in a binary image are assigned to pixels below or above the threshold. It is based on threshold range by statistical calculations. Otsu suggested minimizing the weighted sum of within - class variances of the object and background pixels to establish an optimum threshold [5].

1.1.5 K-means clustering:

K-means clustering is a popular unsupervised learning technique that partitions an image into K distinct clusters based on pixel intensity values. It assigns each pixel to the nearest centroid, iteratively updating centroids until convergence. [3] K-means is computationally efficient and simple to implement, making it effective for basic image segmentation tasks [6]. However, it has limitations in handling noisy images and complex tumor structures, as it relies solely on pixel intensity and can struggle with irregular boundaries.

1.1.6 Fuzzy – c means:

Fuzzy C-means (FCM) is an advanced clustering method that assigns degrees of membership to each data point instead of a hard cluster assignment [7]. This soft clustering approach is

particularly effective for medical image segmentation, where pixel intensities may not be sharply defined. FCM is more flexible than K-means, allowing better handling of overlapping regions and noisy images. However, it is computationally intensive and may require careful parameter tuning to achieve optimal results.

1.1.7 Watershed:

Watershed segmentation is a gradient - based segmentation technique. It considers the gradient map of the image as a relief map [9]. It segments the image as a dam. The segmented regions are called catchment basins. Watershed segmentation solves a variety of image segmentation problem. It is suitable for the images that have higher intensity value. To control over segmentation, marker-controlled watershed segmentation is used. Sobel operator is suitable for edge detection [10]. In marker-controlled watershed segmentation, Sobel operator is used to distinct the edge of the object [11].

1.1.8 Feature Extraction

Feature extraction is process of extracting quantitative information from an image such as colour features, texture, shape, and contrast. Here, we have used discrete wavelet transform (DWT) for extracting wavelet coefficients and Gray-level co-occurrence matrix (GLCM) for statistical feature extraction.

1.1.9 Discrete Wavelet Transform:

The wavelet was used to analyse different frequencies of an image using different scales. Here, we are using discrete wavelet transform (DWT) which is a powerful tool for feature extraction. It was used to extract coefficient of wavelets from brain MR images. The wavelet localizes frequency information of signal function which was important for classification. By using 2D discrete wavelet transform, the images were decomposed into spatial frequency components which were extracted from LL (low–low) sub-bands and since HL(high–low) sub-bands have higher performance when compared to LL (low–low), we have used both LL (low–low) and HL (high–low) for better analysis which describes image text features [21].

1.1.10 Principal Component Analysis:

The most successful techniques that have been used in image recognition and compression is the Principal Component Analysis (PCA) and it is used to reduce the large dimensionality of the data. The basic approach is to compute the Eigen vectors of the covariance matrix of the original data and approximate it by a linear combination of the leading eigenvectors. By using PCA procedure, the test image can be identified by first, projecting the image onto the Eigen space to obtain the corresponding set of weights, and then comparing with the set of weights of the faces in the training set [21].

1.1.11 Classification

In classification tasks, there are often several candidate feature extraction methods available. The most suitable method can be chosen by training neural networks to perform the required classification task using different input features (derived using different methods). The error in the neural network response to test examples provides an indication of the suitability of the corresponding input features (and thus method used to derive them) to the considered classification task. Following are the classification algorithms that have been implemented:

1.1.12 Support Vector Machine:

SVM is one of the classification techniques applied on different fields such as face recognition, text categorization, cancer diagnosis, glaucoma diagnosis, microarray gene expression data analysis [15]. SVM utilizes binary classification of brain MR image as normal, or tumour affected. SVM divides the given data into decision surface, (i.e., a hyper-plane) which divides the data into two classes. The prime objective of SVM is to maximize the margins between two classes of the hyper-plane [16]. Dimensionality reduction and precise feature set given as input to the SVM on the duration of training part as well as during the testing part. SVM is based on binary classifier which employs supervised learning to provide better results.

1.1.13 Convolutional Neural Networks:

Convolutional Neural Networks (CNNs) have proven to be very successful frameworks for image

recognition. In the past few years, variants of CNN models have achieved increasingly better performance for object classification [1]. In this project the following networks have been used for image classification:

1.1.14 ResNet-50:

ResNet-50 is a deep convolutional neural network that is part of the ResNet (Residual Networks) family, designed to tackle the vanishing gradient problem present in deep networks. It consists of fifty layers, including convolutional, batch normalization, ReLU, and fully connected layers. The key innovation in ResNet-50 is the introduction of residual blocks, which use shortcut connections to skip one or more layers, effectively allowing the network to learn identity mappings. This architecture helps in training very deep networks by ensuring that the network can learn even with many layers, leading to improved performance in image classification tasks. ResNet-50 is pre-trained on the ImageNet dataset [20], which contains over a million images across one thousand categories, making it highly effective for a wide range of image recognition applications.

1.1.15 Inception-v3:

Inception-v3 is another powerful convolutional neural network, known for its efficiency and accuracy in image classification. It belongs to the Inception family, which introduces the concept of using multiple filter sizes within the same layer (referred to as Inception modules) to capture distinct types of features. Inception-v3 has 316 layers and includes several advanced techniques such as factorized convolutions, auxiliary classifiers, and batch normalization to improve training speed and accuracy [21]. It is also pre-trained on the ImageNet dataset and can classify images into one thousand distinct categories. The network's design allows it to handle high-dimensional data effectively while reducing computational complexity. In MATLAB, Inception-v3 can be accessed via the `inceptionv3` function, making it a versatile choice for various image processing and classification tasks.

1.2 Research gap:

Addressing the research gap, current segmentation techniques in medical imaging often struggle to balance accuracy and efficiency. While anisotropic diffusion is effective for noise reduction, it can be sensitive to parameter selection, potentially causing over-smoothing or loss of critical edge details. Adaptive techniques capable of handling varying noise levels and inconsistencies across MRI scans are essential.

Combining fuzzy logic and machine learning with anisotropic diffusion shows promise but remains underexplored. These hybrid models can better capture tumour boundaries while minimizing noise. However, developing a robust, generalized solution that performs well across diverse datasets and patient conditions remains challenging. This underscores the need for further research on adaptive parameter selection and real-time optimization.

Additionally, there's limited research on the real-time application of such models in clinical settings, where both speed and interpretability are crucial. Future work should focus on creating automated, adaptive methods that maintain high-quality segmentation without extensive manual adjustments, filling a significant gap in the current medical imaging field.

1.3 Problem statement:

The primary problem addressed by this project is the challenge of accurately identifying and classifying brain tumors from MRI images. Current methods, although advanced, often suffer from issues such as noise, variability in image quality, and inconsistencies across different data sets. These issues can lead to misclassification and inaccuracies, which are critical in medical diagnoses. Existing techniques like traditional machine learning models and image processing methods often require extensive manual tuning and are not always robust enough to handle the diverse conditions found in clinical settings. By integrating machine learning, deep learning models, and advanced preprocessing methods such as anisotropic diffusion, this project seeks to enhance the accuracy and reliability of brain tumor detection and classification. The goal is to develop a more automated and adaptive approach that can effectively process varied MRI images and provide consistent, high-quality results, ultimately aiding medical professionals in making precise diagnoses and improving patient outcomes.

1.3.1 Relevance of the problem statement w.r.t to SDG

The problem addressed in this project is closely aligned with the United Nations Sustainable Development Goals (SDGs), Goal 3: Good Health and Well-being. Accurate and early identification of brain tumours is crucial for effective treatment and better patient outcomes. By improving the precision and reliability of brain tumour detection and classification through advanced machine learning and deep learning techniques, this project directly contributes to enhancing the quality of healthcare services.

Additionally, by developing automated and adaptive methods that can handle diverse MRI image qualities and reduce the need for extensive manual tuning, the project aims to make advanced diagnostic tools more accessible and usable in various clinical settings, including those in resource-limited areas. This supports the broader aim of SDG 3 to ensure healthy lives and promote well-being for all at all ages by providing innovative solutions to complex health challenges.

By addressing these critical healthcare needs, the project not only advances medical imaging technologies but also contributes to the global effort to improve health outcomes and reduce health disparities.

2. PROJECT OBJECTIVE

2.1 Background

Brain tumours are abnormal growths of cells within the brain, which can be either benign or malignant. These tumours disrupt normal brain functions and are challenging to diagnose accurately without advanced medical imaging techniques. Magnetic Resonance Imaging (MRI) is widely utilized for detailed visualization of brain tissues and the identification of tumours. In this project, we employ MATLAB for the automated detection, segmentation, and classification of brain tumours using advanced image processing and machine learning methods. By integrating techniques like ResNet-50, K-means clustering, Fuzzy C-means, and other segmentation algorithms, this system aims to support neurosurgeons, radiologists, and healthcare professionals in diagnosing brain tumours more effectively. The dataset comprises MRI scans sourced from public cancer imaging archives, enabling a comprehensive evaluation of the proposed methods. The use of MATLAB provides an efficient platform for implementing and testing these methods, focusing on enhancing diagnostic accuracy and reducing the time required for manual analysis.

2.2 Problem Definition

The primary goal of this study is to develop an automated system capable of accurately detecting and classifying brain tumours from MRI scans. The system aims to identify the presence of a tumour and distinguish between different tumour types, including glioma, meningioma, pituitary tumour, and no tumour, using a hybrid deep learning approach. This involves preprocessing, segmentation using methods like K-means and Fuzzy C-means, and classification using a pre-trained ResNet-50 model. The challenge lies in achieving robust performance despite the variability in MRI images and tumour characteristics.

2.3 Motivation

The motivation behind this project stems from the need for a more reliable, efficient, and automated approach to brain tumour detection. Manual analysis of MRI scans is time-consuming and prone to human error, especially when distinguishing between diverse types of

tumours. An automated system would aid healthcare specialists by reducing diagnostic time and providing consistent and objective results. With an increasing number of MRI scans being conducted globally, there is a growing demand for tools that can assist radiologists in early detection and decision-making, improving patient outcomes and reducing healthcare costs.

2.4 Scope

This project aims to develop a comprehensive image processing pipeline in MATLAB for the detection, segmentation, and classification of brain tumours. The system will utilize a combination of classical segmentation techniques (like K-means clustering and Fuzzy C-means) and modern deep learning methods (such as ResNet-50) for classification.

Implementation of various segmentation techniques to enhance tumour visualization. A hybrid deep learning approach for robust classification of MRI scans into glioma, meningioma, pituitary tumour, and no tumour categories. A user-friendly MATLAB interface for real-time processing and visualization, including 3D tumour visualization. Evaluation of the system's performance using accuracy, F1 score, and additional metrics tailored for medical image analysis.

The system is designed to be adaptable for future enhancements, including the potential integration of additional segmentation methods, larger datasets, and more complex neural network architectures. By providing an end-to-end automated solution, the project seeks to contribute a valuable tool for assisting in clinical decision-making and improving the reliability of brain tumour screening procedures.

3. PROPOSED WORK

3.1 Design approach and methodology:

The system model for brain tumours detection and classification is structured into a multi-phase pipeline that integrates image preprocessing, segmentation, feature extraction, and classification. This design approach leverages both traditional image processing techniques and modern deep learning models to provide a comprehensive solution for identifying and classifying brain tumors from MRI scans. Below is the description of the complete system model.

Algorithm Overview:

1. Data Acquisition:
 - Load the MRI dataset containing images of four categories: glioma, melanoma, pituitary tumour, and no tumour.
2. Preprocessing:
 - Resize the images to a standard size (256x256 pixels).
 - Apply noise reduction using Gaussian filtering.
 - Convert images to grayscale for segmentation.
3. Segmentation:
 - Otsu's Thresholding: For initial binarization of the image.
 - Canny Edge Detection: To highlight tumour edges and contours.
 - K-means Clustering: To partition the image into distinct clusters for region analysis.
 - Fuzzy C-means: For soft clustering and improved delineation of the tumor area.
 - Watershed Segmentation: To refine tumour boundaries based on intensity gradients.
4. Feature Extraction:
 - Extract shape-based features (area, perimeter, and solidity).
 - Extract texture features using GLCM (Gray Level Co-occurrence Matrix).
5. Classification:
 - Use SVM for binary classification (tumour vs. no tumour).
 - Utilize fine-tuned deep learning models for multi-class classification of tumour types
 - Use deep learning models (ResNet-50, Inception V3) for automated high-level feature extraction.
6. Performance Evaluation:
 - Calculate metrics like accuracy, precision, recall, F1 score, and confusion matrix for model evaluation.
7. Visualization:
 - Display segmented images and results.
 - 3D visualization of detected tumour using Fuzzy C-means segmented image.

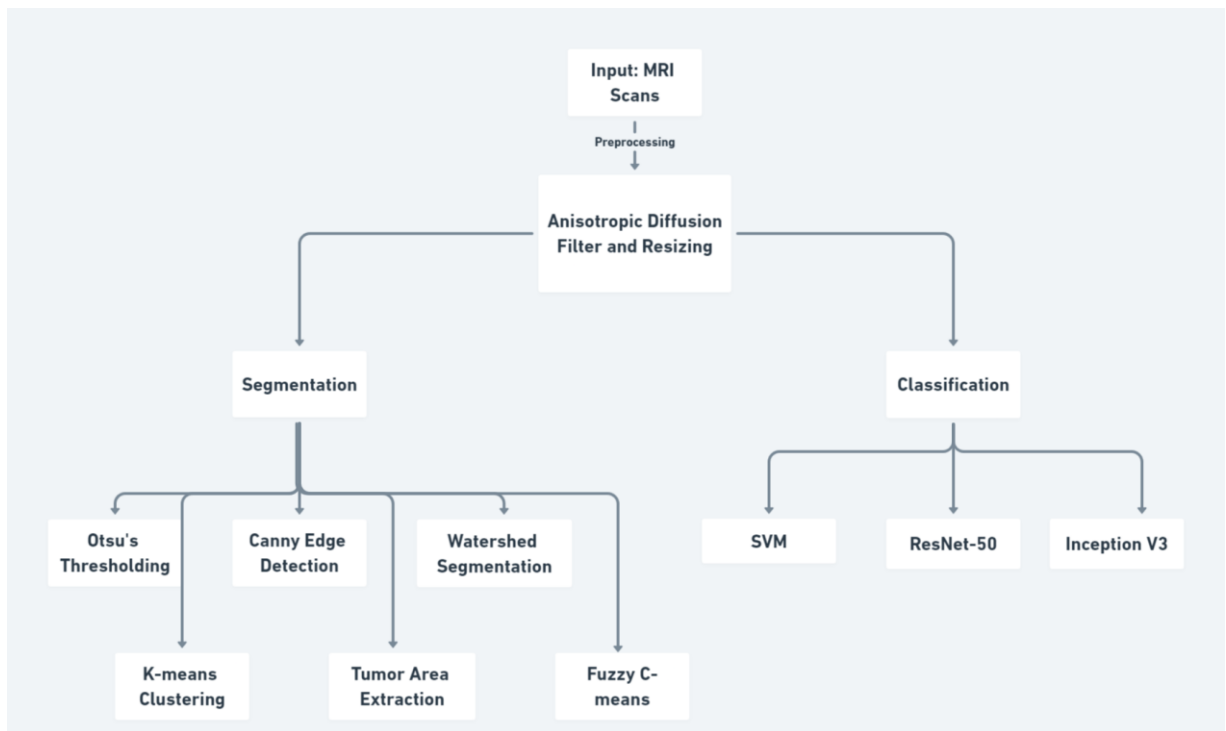


Figure 1: Flowchart of the project

User case diagram:

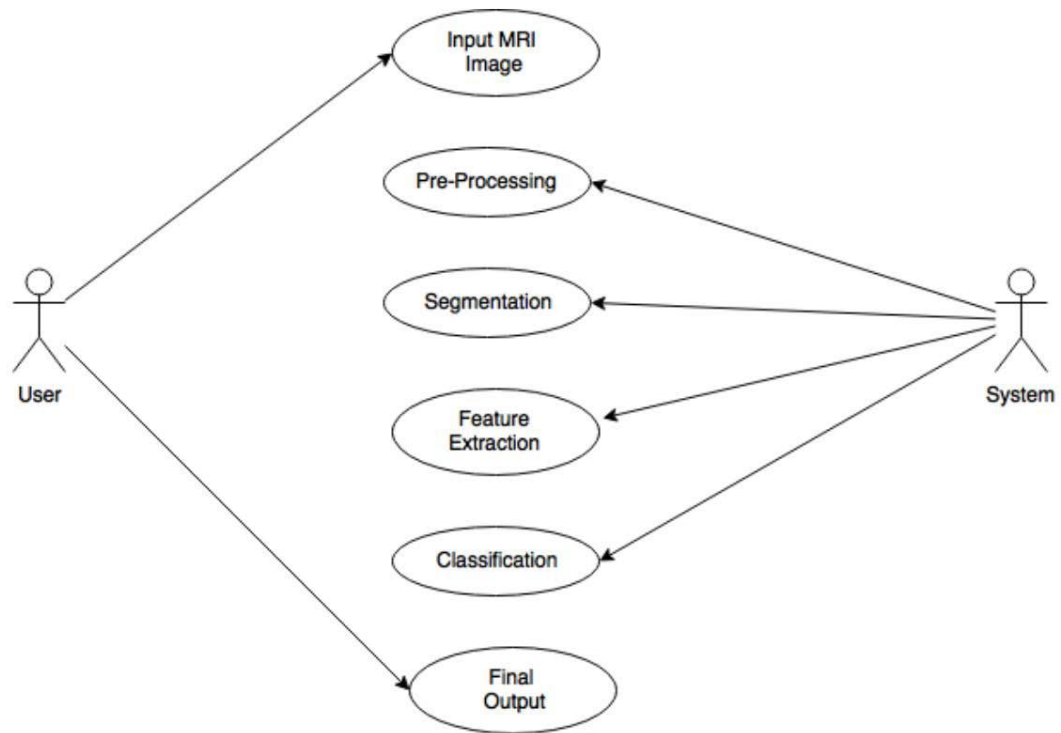


Figure 2: User case diagram

3.2 TECHNICAL DESCRIPTIONS

3.2.1 Dataset Used for Analysis

The dataset used for this analysis consists of MRI images representing four distinct categories: glioma, meningioma, pituitary tumour, and no tumour. The images were collected from publicly available cancer imaging archives, ensuring a diverse and comprehensive set of samples for evaluation. The dataset includes approximately 14,000 images, with each category represented by a considerable number of samples to facilitate effective training and testing of the classification models.

The MRI scans in the dataset have varying resolutions and formats (e.g., .jpg, .png), and they encompass different scanning conditions, noise levels, and patient demographics. This variability presents a realistic challenge for the automated detection and classification of brain tumours, highlighting the importance of robust preprocessing, segmentation, and classification techniques. For consistency, all images were resized to a fixed dimension of 256×256 pixels during preprocessing to ensure compatibility with the neural network input requirements.

Key Characteristics of the Dataset:

1. **Number of Classes:** 4 (Glioma, Meningioma, Pituitary Tumour, No Tumour).
2. **Total Number of Images:** ~14,000.
3. **Image Source:** Public cancer imaging databases and pathology lab archives.
4. **Image Modality:** T1-weighted MRI scans.
5. **Image Format:** .jpg, .png.
6. **Resolution:** Standardized to 256×256 pixels for analysis.

Dataset Split:

- The dataset was divided into 80% for training and 20% for testing, ensuring a balanced representation of each category in both subsets. This split was randomized to minimize any potential bias and to enhance the generalizability of the model.

3.2.2 Otsu algorithm:

Otsu's Thresholding is a global image segmentation technique used to automatically determine the optimal threshold for separating foreground (objects of interest) from the background. It is

based on maximizing the variance between different classes in the image, making it effective for images with distinct intensity distributions. Otsu's method has been widely applied in medical image processing for segmenting tumour regions and other structures of interest.

The process of Otsu's Thresholding can be broken down into five steps:

1. **Image Resizing:** The input image is resized to a standard size to ensure consistency and to facilitate further processing.
2. **Automatic Threshold Calculation:** Otsu's method calculates the optimal threshold value that maximizes the between-class variance, effectively separating the foreground from the background.
3. **Binarization:** The image is converted into a binary format using the computed threshold, where pixels are classified as either foreground (white) or background (black).
4. **Noise Removal:** Small, insignificant objects that may be considered noise are removed from the binary image to retain only the significant regions.
5. **Segmentation Output:** The final segmented image is displayed, highlighting the region of interest (e.g., potential tumour areas), and saved for further analysis.

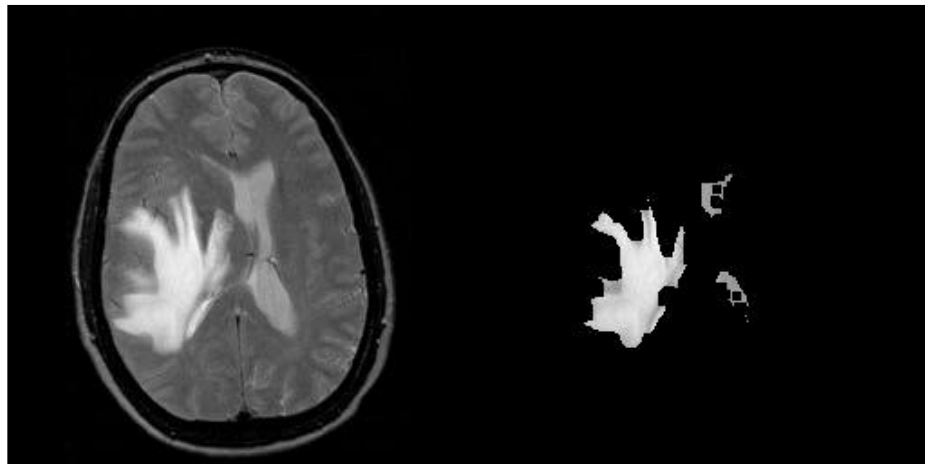


Figure 3: Output image from OTSU algorithm

3.2.3 Canny algorithm:

Canny edge detection is a technique used to extract useful structural information from different vision objects while significantly reducing the amount of data to be processed. It is widely applied in various computer vision systems. The Canny edge detection algorithm can be broken

down into five distinct steps:

1. **Apply Gaussian Filter:** The first step involves smoothing the image using a Gaussian filter to remove any noise. This step is crucial because noise can lead to false edge detection.
2. **Find Intensity Gradients:** The next step is to compute the intensity gradients of the image. This helps in identifying areas where the intensity changes sharply, which typically correspond to edges.
3. **Non-Maximum Suppression:** To refine the edge detection, non-maximum suppression is applied. This process involves suppressing any pixel value that is not considered a part of an edge, effectively reducing the thickness of edges to one pixel wide.
4. **Double Threshold:** This step uses two threshold values (high and low) to categorize the edges. Strong edges are those pixel values that are above the high threshold, while weak edges are those between the high and low threshold values. This categorization helps in distinguishing significant edges from noise.
5. **Edge Tracking by Hysteresis:** Finally, edge tracking by hysteresis is performed. This step ensures that weak edges that are connected to strong edges are retained, while the rest are discarded. This results in a more accurate and continuous edge detection.

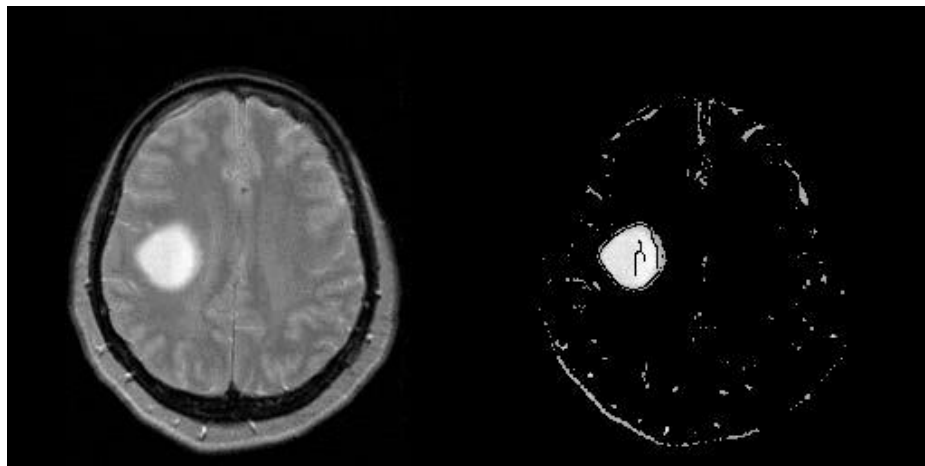


Figure 4: Output image from Canny segmentation

3.2.4 Fuzzy c means

Fuzzy C-Means (FCM) thresholding is a clustering technique used for image segmentation. It segments the image by assigning membership values to each pixel, indicating the degree to

which each pixel belongs to a cluster. This method allows for more flexible and accurate segmentation compared to hard thresholding methods. The implementation involves the following steps:

1. **Check for Image Data:** The code first checks if the image data (ImgData) exists within the handles structure. If the image data is not present, an error dialog is displayed, prompting the user to load or preprocess the image first.
2. **Image Resizing:** The input image is resized to a fixed size of 256x256 pixels to standardize the dimensions for processing.
3. **Normalization:** The image is normalized to grayscale in the range [0, 1] using the `mat2gray` function. This step ensures that the pixel intensity values are within a consistent range for thresholding.
4. **FCM Thresholding:** The normalized grayscale image is subjected to FCM thresholding using two different methods. The `fcmthresh` function is used to perform the thresholding:
 - **Method 0:** The first method (`fcmthresh(fim, 0)`) applies the initial FCM thresholding technique.
 - **Method 1:** The second method (`fcmthresh(fim, 1)`) applies an alternative FCM thresholding technique.

The resulting segmented binary images (`bwfim0` and `bwfim1`) and their corresponding threshold levels (`level0` and `level1`) are obtained.

5. **Visualization:** The original image and the two segmented images are displayed using the subplot function

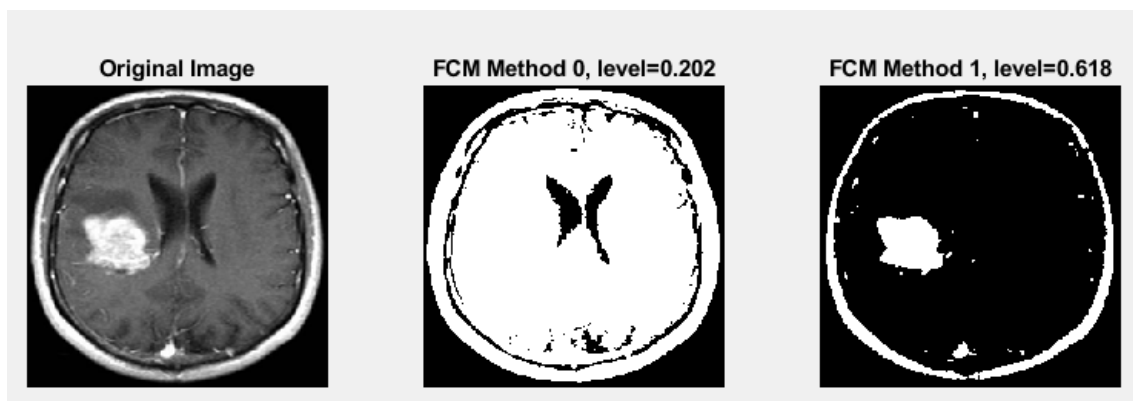


Figure 5: Output Image from Fuzzy – c means

3.2.5 K- means clustering:

K-means clustering is a technique used for image segmentation. It segments the image by clustering pixels into distinct groups based on their intensity values. The implementation involves the following steps:

1. Check for Image Data: The code first checks if the image data (ImgData) exists within the handles structure. If the image data is not present, an error dialog is displayed, prompting the user to preprocess the image first.
2. Image Resizing: The input image is resized to a fixed size of 256x256 pixels to standardize the dimensions for processing.
3. Convert to Grayscale: The image is converted to grayscale to simplify the data and reduce computational complexity.
4. Reshape Image Data: The grayscale image data is reshaped into a one-dimensional array suitable for clustering.
5. K-means Clustering: The reshaped image data is subjected to K-means clustering with a specified number of clusters (in this case, four clusters). The algorithm assigns each pixel to one of the clusters based on its intensity value.
6. Reshape Clustered Indices: The clustered indices are reshaped back to the original image size to create a segmented image.
7. Visualization: The clustered image and individual clusters are displayed:
 - The clustered image is displayed with a title indicating it is the result of K-means clustering.
 - Each individual cluster is displayed in separate subplots with titles indicating the cluster number.

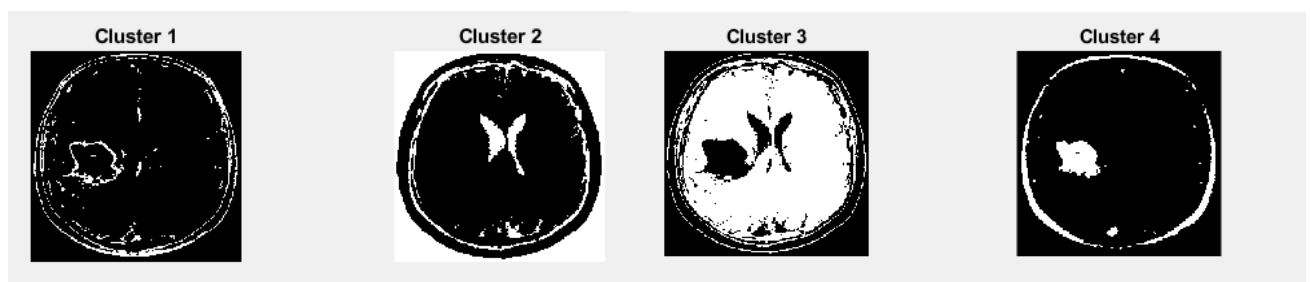


Figure 6: Output image from K-means clustering

3.2.6 Watershed algorithm:

Watershed segmentation is a technique used to separate different objects in an image. It uses the gradient magnitude of an image to identify and segment regions. The implementation

involves the following steps:

1. **Check for Image Data:** Verify the presence of image data (GrayImg) in the handles structure.
2. **Image Resizing:** Standardize the input image to 256x256 pixels.
3. **Threshold Calculation:** Compute a threshold value using an initial threshold ($t_0 = 60$) and the average intensity of the input image.
4. **Apply Thresholding:** Threshold the image to differentiate between foreground and background pixels.
5. **Apply Sobel Filter:** Compute the gradient magnitude using horizontal and vertical Sobel filters.
6. **Apply Watershed Transform:** Segment regions using the watershed transform, producing a label matrix.
7. **Convert to RGB Image:** Convert the label matrix to an RGB image for visualization.
8. **Visualization:** Display the segmented image.

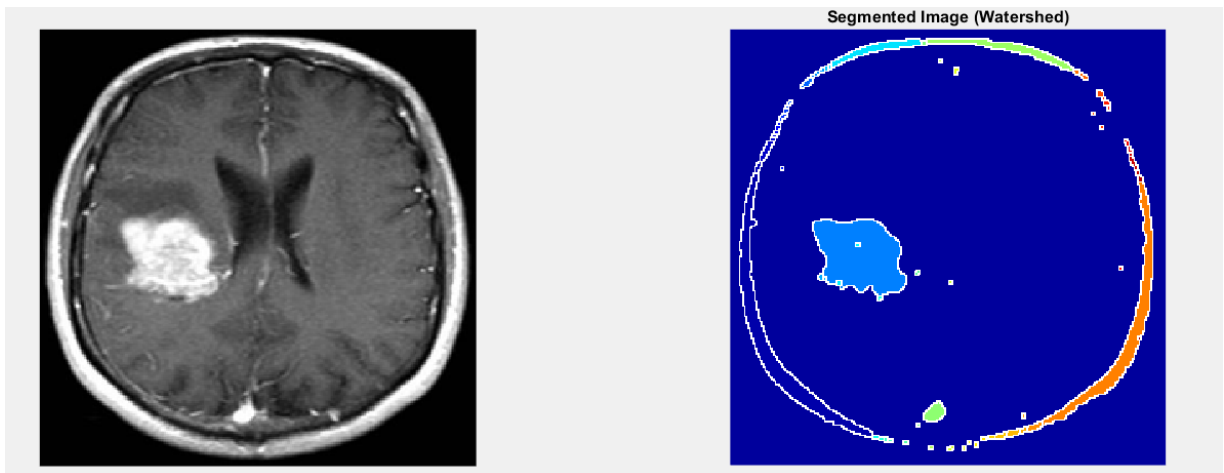


Figure 7: Output image from Watershed algorithm

3.2.7 Tumour area:

This implementation applies various image processing techniques to detect and segment a tumour in each image. The process involves the following steps:

1. **Check for FCM Thresholded Image:** Verify if the FCM thresholded image (FCMImg1)

exists within the handles structure.

2. **Image Resizing:** Resize the FCM thresholded image to 256x256 pixels for standardization.
3. **Convert to uint8:** Scale the logical image to the range [0, 255] for compatibility with subsequent processing steps.
4. **Contrast Enhancement:** Enhance the image contrast using Contrast Limited Adaptive Histogram Equalization (CLAHE).
5. **Smoothing:** Apply Gaussian filtering to reduce noise in the enhanced image.
6. **Otsu's Thresholding:** Use Otsu's method to binarize the smoothed image.
7. **Morphological Operations:** Perform morphological operations to remove noise and label connected components.
8. **tumour Detection:** Detect the tumour based on solidity and area properties. Use a dynamic area threshold to identify the tumour.
9. **Bounding Box and Outline:** Draw a bounding box around the detected tumour and outline it using morphological operations.
10. **Visualization:** Display the original image with the bounding box, the tumour alone, the tumour outline, and the detected tumour with the outline.

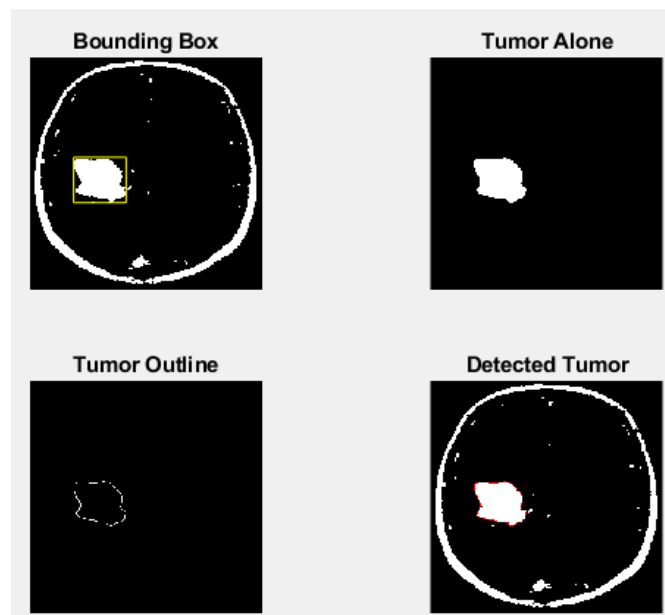


Figure 8: Output image from tumour area

3.2.8 Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA):

The discrete wavelet transform (DWT) is a powerful implementation of the WT using the dyadic scales and positions. The fundamentals of DWT are introduced as follows. Suppose $x(t)$ is a

square-integrable function, then the continuous WT of $x(t)$ relative to a given wavelet $\psi(t)$ is defined as

$$W_{\psi}(a, b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}(t) dt \quad (1)$$

where

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-a}{b}\right) \quad (2)$$

Here, the wavelet $\psi_{a,b}(t)$ is calculated from the mother wavelet $\psi(t)$ by translation and dilation: a is the dilation factor and b the translation parameter (both positive numbers). There are several distinct kinds of wavelets which have gained popularity throughout the development of wavelet analysis. The most important wavelet is the Harr wavelet, which is the simplest one and often the preferred wavelet in a lot of applications.

GLCM is a widely used method for medical image analysis, classification. This method gives us information about relative position of two pixels with respect to each other. The GLCM is then created by counting the number of occurrences of pixel pairs at a certain distance. To compute the GLCM matrix for an image $f(i, j)$, a distance vector $d=(x, y)$ is defined. The (i, j) th element of the GLCM matrix P is defined as the probability that grey levels i and j occur at distance d and angle θ , then extracting texture features from GLCM matrix P . Four angles (0, 45, 90, 135) and four distances (1, 2, 3, 4) can be used to calculate the co-occurrence matrix.

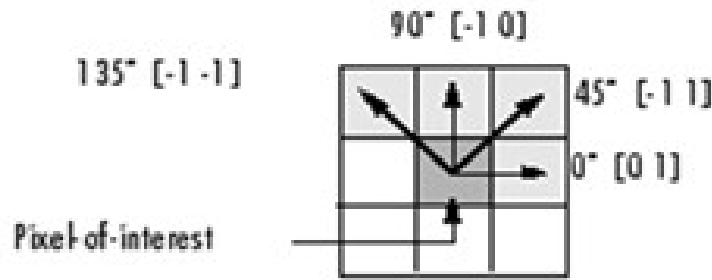


Figure 9: Calculation of co-occurrence matrix in GLCM

1. Correlation:

It measures the linear dependency of grey levels of neighbouring pixels. It is defined in Eq.1

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i - \mu)(j - \mu)}{\sigma^2}$$

Equation 1: Correlation

2. Contrast

Also called the sum of Square Variance. It defers the calculation of the intensity contrast linking pixel and its neighbour over the whole image. It is defined in Eq. 2

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij} (i - j)^2$$

Equation 2: Contrast

3. Energy

It makes use for the texture that calculates orders in an image. It gives the sum of square elements in GLCM. It is defined in Eq. 3

$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2$$

Equation 3: Energy

4. Homogeneity

It passes the value that calculates the tightness of distribution of the elements in the GLCM to the GLCM diagonal. It is defined in Eq. 4

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1 + (i - j)^2}$$

Equation 4: Homogeneity

5. Mean

Defined as the mean of the pixel values of the input image. It is defined in Eq. 5

$$Mean = \sum_{i,j=0}^{N-1} i(P_{i,j})$$

Equation 5: Mean

6. Standard Deviation

It is defined as the dispersion of the pixel in consideration from the mean of the pixels of the

input image. It is defined in Eq. 6

$$\text{Standard Deviation} = \sqrt{\sigma_i^2} \quad \text{Equation 6: Standard Deviation}$$

7. Entropy

It shows the amount of information of the image that is needed for the image compression.

Entropy measures the loss of information or message in a transmitted signal and measures the image information. It is defined in Eq. 7

8. Root Mean Square (RMS)

RMS is calculated on a set of pixels by taking the square of each pixel, calculating the sum of those squares, and taking the square root. The result is scaled by the number of pixels. RMS gives an accurate measurement of the amount of noise present. It is defined in Eq. 8

$$\text{RMS noise} = \sqrt{\frac{\sum_{i=1}^n (X_i - \frac{\sum_{i=1}^n X_i}{n})^2}{n}} \quad \text{Equation 8: Root Mean Square}$$

9. Variance

It is the expectation of the squared deviation of a pixel from its mean. It is defined in Eq. 9

$$\text{Variance} = \sum_{i,j=0}^{N-1} P_{i,j} (i - \mu_i)^2 \quad \text{Equation 9: Variance}$$

10. Inverse Difference Movement (IDM)

Inverse Difference Moment (IDM) is the local homogeneity. It is high when local gray level is uniform and inverse GLCM is high. It is defined in Eq. 10

$$\text{IDM} = \frac{\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} P_{i,j}}{1 + (i-j)^2} \quad \text{Equation 10: Inverse Difference Movement}$$

3.2.9 Support Vector Machine (SVM)

Support vector machines (SVMs) are a type of supervised learning models along with associated

learning algorithms that analyse data and recognize various patterns, used for classification analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two classes, malignant and benign forms the output, making it a non-probabilistic binary linear classifier. Now that there are set of training examples at hand, each marked as belonging to one of two categories, an SVM training algorithm constructs a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories is divided by a clear gap that is as wide as possible. Newer examples are then plotted into it and then predicted to belong to a category based on which side of the gap they fall on.

More formally, a support vector machine constructs a hyper plane or set of hyper planes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

A SVM takes a set of feature vectors as input, generates a training model after scaling, selecting, and validating, and generates a training model as the output. The following figure represents the training process of an SVM:

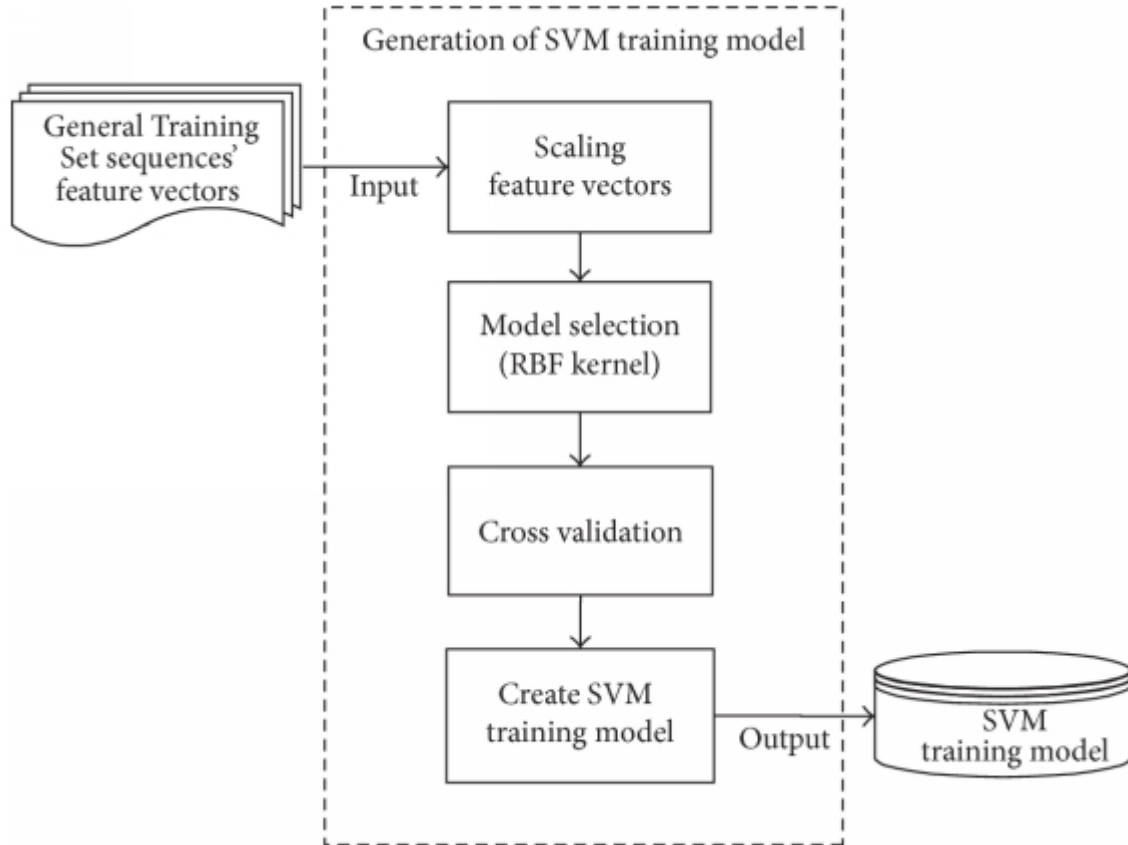


Figure 10: Training a SVM model

3.2.10 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are like traditional neural networks which are made of neurons with learnable weights and biases. Each neuron receives several inputs, takes a weighted sum over them, pass it through an activation function and responds with an output [21].

The CNN algorithm is a multilayer perceptron that is the distinctive design for identification of two-dimensional image information. It has the following layers: input layer, convolution layer, sample layer and output layer. Each neuron parameter is set to the same parameter, namely, the sharing of weights, i.e., each neuron with the same convolution kernels to deconvolution image. The figure below illustrates the process applied during CNN [21].

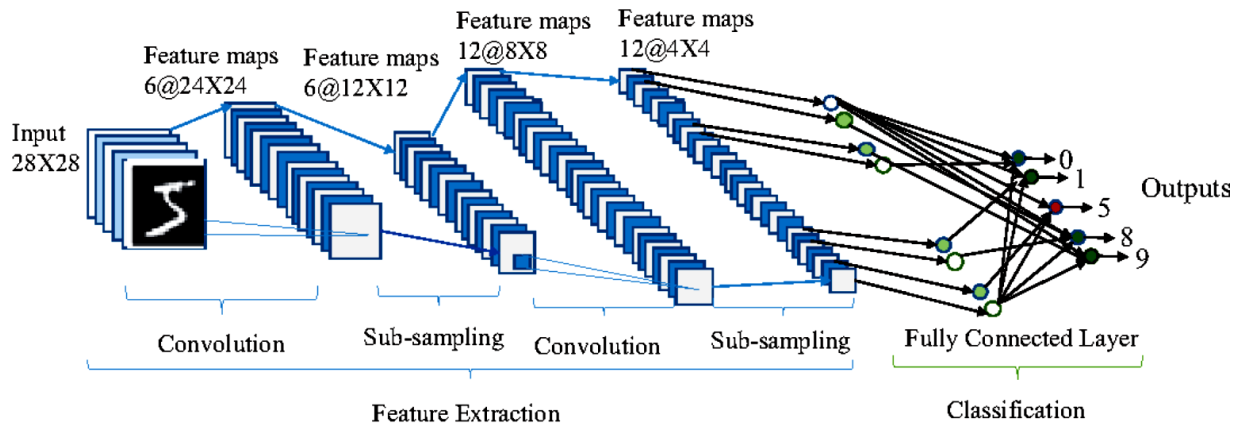


Figure 11: CNN block diagram

The CNN algorithm has two main processes: convolution and sampling.

The convolution process use a trainable filter F_x for the deconvolution of the input image (the first stage is the input image, the second input after the convolution is the feature image of each layer, namely the feature map), and then adds a bias b_x , which results in the convolution layer C_x .

The sampling process puts n pixels of each neighbourhood through pooling steps to become a pixel, and then weighting by scalar weighting $W_x + 1$, adding the bias $b_x + 1$, and then the activation function produces a narrow n time feature map $S_x + 1$.

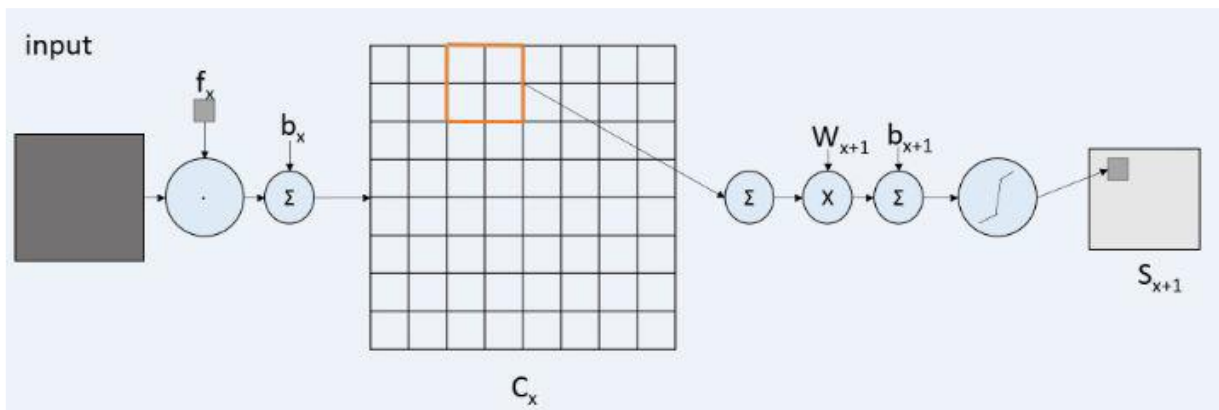


Figure 12: Working of CNN

The main idea of the CNN algorithm is the usage of the local receptive field, the weight sharing, and the sub sampling by time or space for feature extraction and reducing the size of the training parameters. CNN is advantageous as it explicitly avoids feature extraction and tries to implicitly

learn from the training data.

The neuron weights are the same on the surface of the feature mapping, thus enabling the network to learn in parallel, and helping to reduce the complexity of the network. Further, adopting the sub sampling structure by time or space, can achieve some degree of robustness, scale, and deformation displacement.

We are using transfer learning of two pretrained network which is available in MATLAB already

3.2.11 ResNet-50

ResNet-50 is a convolutional neural network (CNN) architecture that belongs to the ResNet (Residual Networks) family. It was introduced by Kaiming He et al. at Microsoft Research Asia in 2015². The key innovation of ResNet-50 is the use of residual blocks and skip connections to enable the training of very deep networks. Here are some key features:

- **Depth:** ResNet-50 consists of fifty layers, including forty-eight convolutional layers, one max-pooling layer, and one average-pooling layer.
- **Residual Blocks:** These blocks use shortcut connections to allow the gradient to flow through the network more effectively, mitigating the vanishing gradient problem.
- **Bottleneck Design:** Each residual block includes a bottleneck design with one-by-one, three-by-three, and one-by-one convolutions to reduce the number of parameters and computational complexity.
- **Applications:** ResNet-50 is widely used for image classification, object detection, and other computer vision tasks.

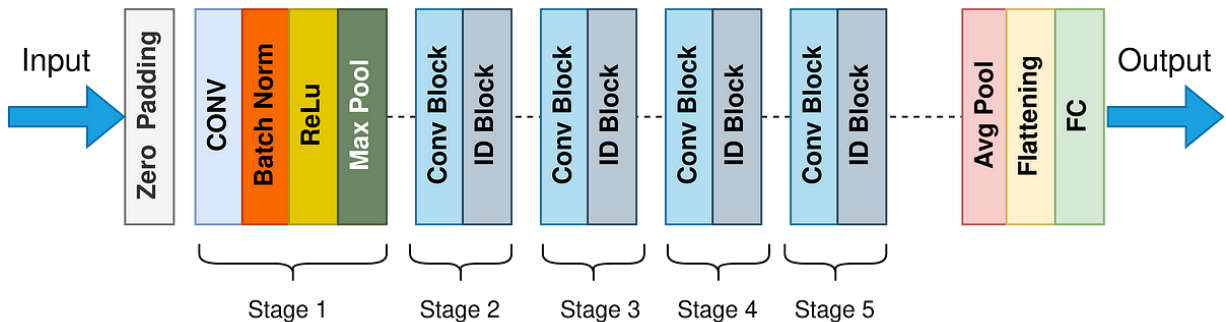


Figure 13: Architecture of Resnet - 50

3.2.12 Inception V3

Inception V3 is another CNN architecture developed by researchers at Google. It is part of the Inception family, which was first introduced as GoogLeNet in 2014. Inception V3 builds on the previous versions by incorporating several optimizations for better efficiency and accuracy. Key features include:

- **Inception Modules:** The architecture uses multiple parallel convolutional filters of varied sizes (1x1, three-by-three, five-by-five) within the same layer to capture features at various scales.
- **Factorized Convolutions:** Inception V3 uses factorized convolutions to reduce the computational cost.
- **Auxiliary Classifiers:** These classifiers are used during training to propagate label information lower down the network and help with convergence.
- **Batch Normalization:** This technique is used to stabilize the learning process and improve convergence.
- **Applications:** Inception V3 is used for image classification, object detection, and other computer vision tasks.

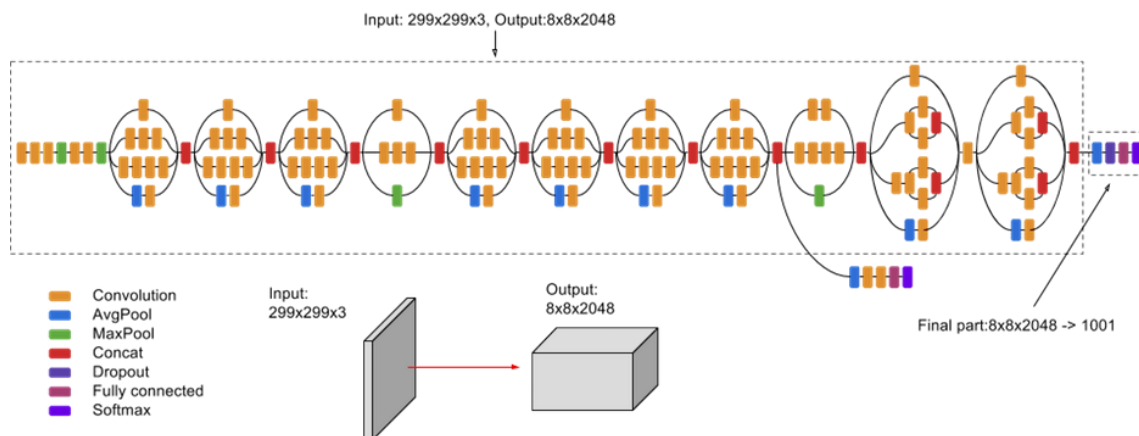


Figure 14: Architecture of Inception v3

4. HARDWARE/SOFTWARE TOOLS USED

Software Requirements:

- MATLAB 2017a or later
- Dataset obtained from pathology labs
- Online dataset from www.cancerimagingarchive.net
- Microsoft Office

Hardware Requirements:

- Intel Dual Core Dual Processor or advanced version
- Minimum 8GB of RAM
- Minimum 1 GB of Hard disk Space

5. RESULT ANALYSIS:

Segmentation Method	Accuracy
Otsu Thresholding	0.71
Canny Edge Detection	0.86
Watershed Segmentation	0.92
Fuzzy C-means (FCM)	0.92
K-means Clustering (Cluster 1)	0.64
K-means Clustering (Cluster 2)	0.94
K-means Clustering (Cluster 3)	0.38
K-means Clustering (Cluster 4)	0.68
Tumour Bounding Box	0.92

Table 1: Accuracy of segmentation techniques

SVM training and accuracy:

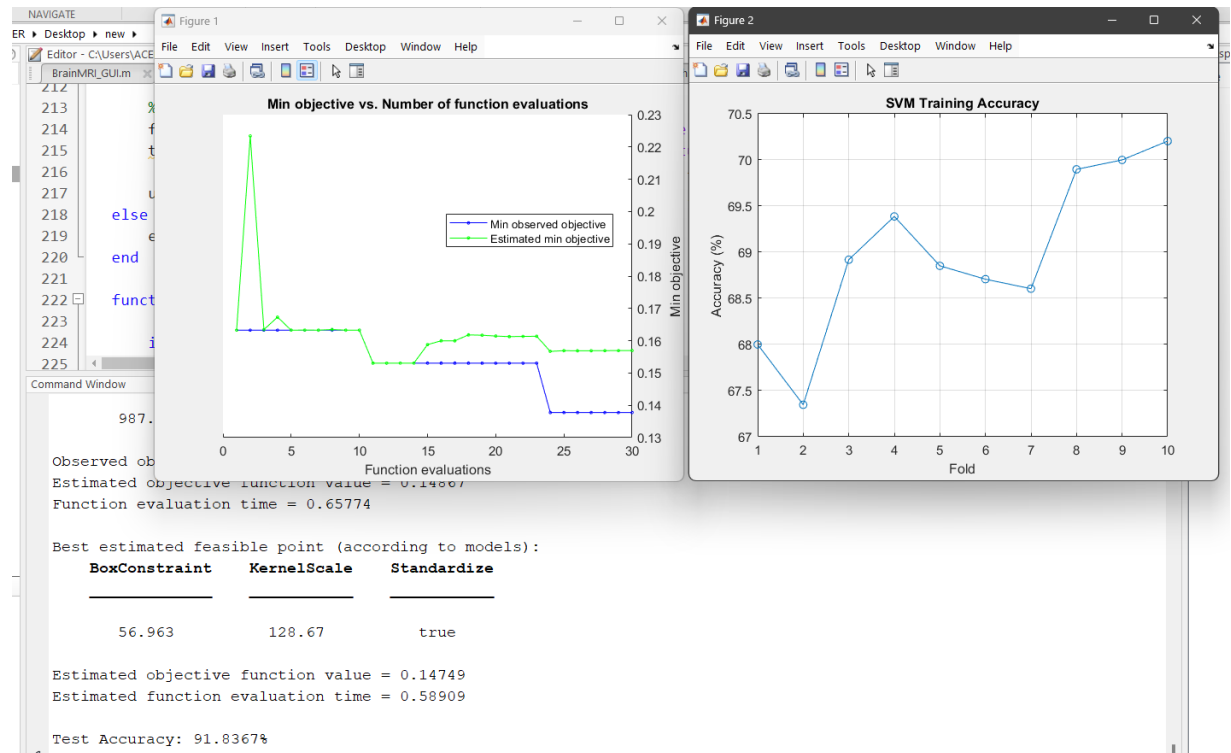


Figure 15: SVM training image

CNN training accuracy and validation:

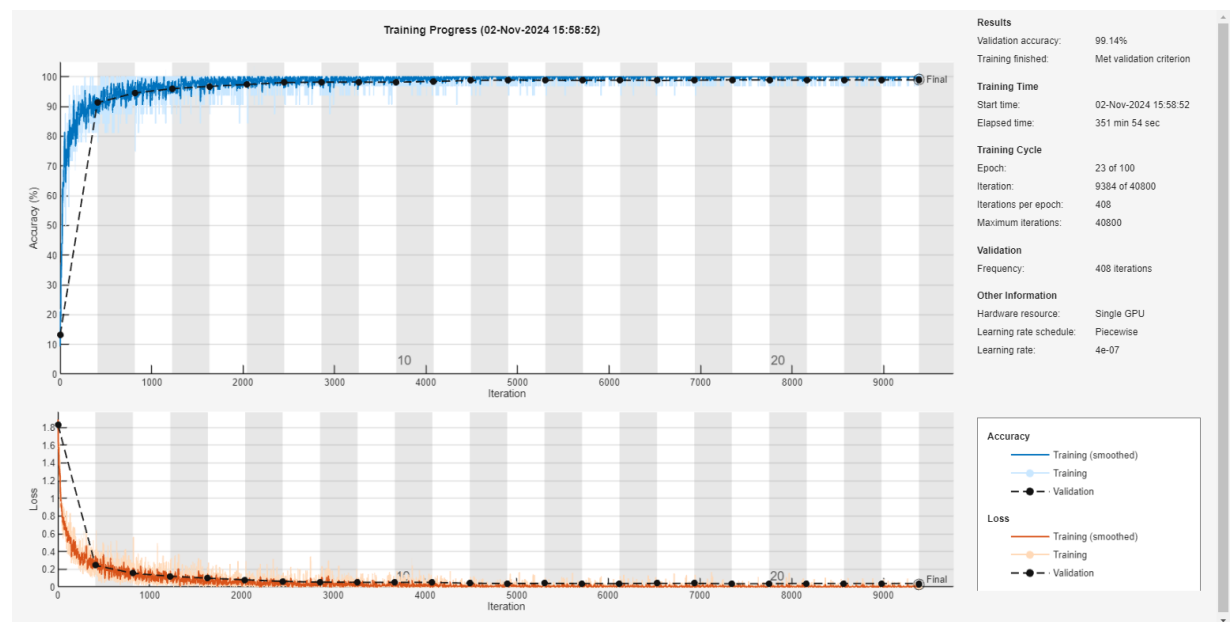


Figure 16: Training accuracy and validation of Resnet 50

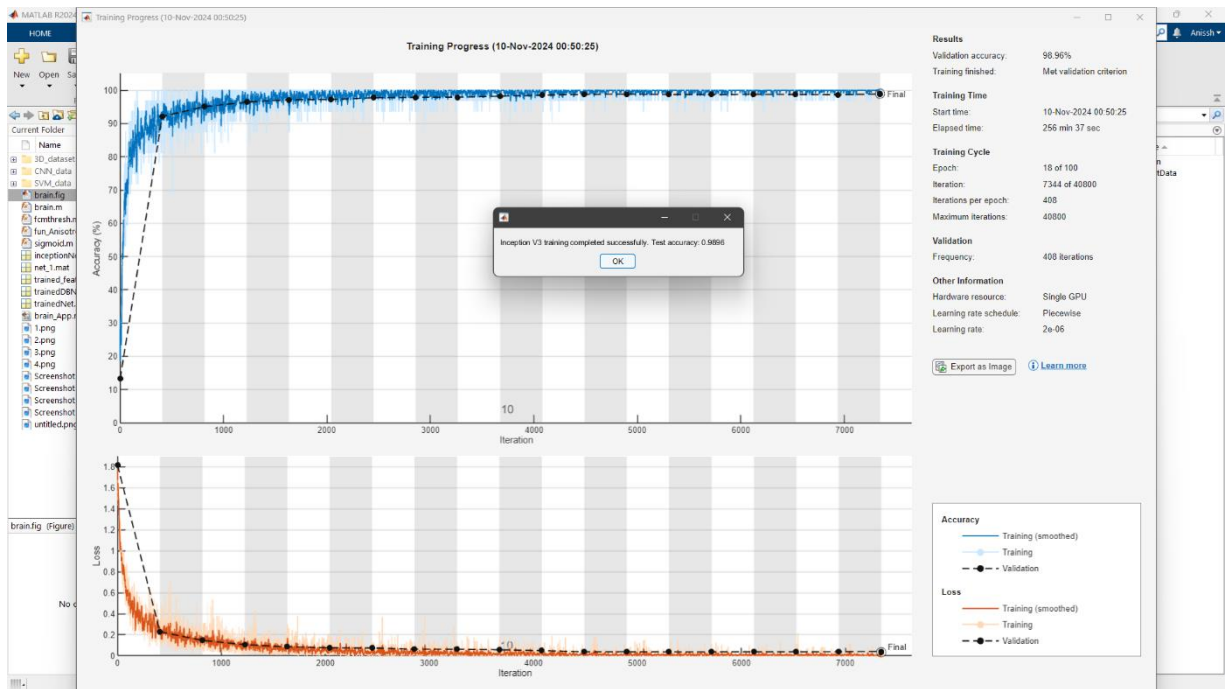


Figure 17: Training accuracy and validation of Inception v3

Resnet 50: 99.14%

Inceptionv3: 98.96%

6. CONCLUSION AND FUTURE WORK

6.1 Summary

The project aimed to develop an efficient automated system for brain tumour detection and classification using advanced image processing, segmentation, and machine learning techniques. The implemented approach utilized anisotropic diffusion for preprocessing, followed by multiple segmentation methods such as Otsu's thresholding, Canny edge detection, watershed segmentation, fuzzy c-means (FCM), and K-means clustering. Feature extraction was carried out using Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Gray Level Co-occurrence Matrix (GLCM). The classification was performed using SVM, ResNet-50, and Inception V3 networks, leading to significant accuracy in detecting and classifying tumours into benign or malignant categories. This system demonstrated its potential as a reliable tool for assisting radiologists and neurosurgeons in early diagnosis, which can help improve patient outcomes.

6.2 Limitations and Constraints

Despite its promising results, the project faced certain limitations:

- **Dataset Imbalance:** The dataset contained fewer samples for certain tumour categories, which could impact the classification performance and generalization of the model.
- **Segmentation Variability:** Different segmentation techniques yielded varied accuracy levels, and the performance of the segmentation methods was influenced by noise and image quality.
- **Computational Complexity:** The use of deep learning models such as ResNet-50 and Inception V3 required substantial computational power, which posed challenges when running on standard hardware.
- **Lack of 3D Data:** The project used 2D MRI slices, which may not capture the full extent of the tumour in three dimensions, potentially affecting the accuracy of tumour volume estimation.

6.3 Improvement / Future Work

To address these limitations and enhance the system, several improvements can be made in future work:

- **Utilization of 3D MRI Scans:** Incorporating 3D MRI data can provide a more comprehensive view of the tumour, allowing for better volume estimation and segmentation accuracy.
- **Integration of Hybrid Models:** Exploring hybrid architectures that combine multiple

CNN models, or integrating deep learning with traditional machine learning techniques, could improve classification performance.

- **Augmented and Synthetic Data:** Employing data augmentation and synthetic data generation techniques can help mitigate dataset imbalance issues and enhance model robustness.
- **Real-time Processing:** Optimizing the computational efficiency of the models will be essential for implementing the system in real-time clinical settings, making it practical for use in hospitals.
- **Explainable AI:** Introducing explainability features in the model can help radiologists understand the decision-making process, increasing trust and adoption of the system in clinical environments.

7. WORK PLAN

7.1 Timeline

Task	Duration	Milestone Achieved
Project Ideation and Research	Week 1-2	Finalized project scope and objectives.
Dataset Collection and Preprocessing	Week 3-4	Completed data gathering and preprocessing.
Segmentation Technique Implementation	Week 5-7	Implemented various segmentation methods (Otsu, Canny, FCM, Watershed, K-means).
Feature Extraction and Classification	Week 8-10	Developed feature extraction (DWT, PCA, GLCM) and classifiers (SVM, ResNet-50, Inception V3).
Model Evaluation and Result Analysis	Week 11-12	Completed performance metrics evaluation for segmentation and classification.
Report Writing and Presentation Preparation	Week 13-14	Documented project findings and prepared for final presentation.

Table 2: Timeline of the project

7.2 Individual Contribution

The entire project, including research, dataset preparation, implementation of preprocessing, segmentation, feature extraction, model training, and evaluation, was carried out by a single individual. The contributor handled all tasks independently:

- Conducted comprehensive research on existing brain tumour detection methodologies.
- Collected and pre-processed the MRI dataset for analysis.
- Implemented various segmentation techniques (Otsu, Canny Edge, Watershed, FCM, and K-means clustering).
- Extracted features using Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Gray Level Co-occurrence Matrix (GLCM).
- Developed and trained classification models using SVM, ResNet-50, and Inception V3.
- Evaluated the model's performance using accuracy metrics.
- Prepared the final report and presentation material.

8. COST ANALYSIS

This cost analysis covers the expenses involved in the development, testing, and implementation of the project. The analysis includes the costs related to software, hardware, data acquisition, and other operational aspects.

Item	Cost (Rupees)	Description
MATLAB Software License	0 (Academic)	Academic version of MATLAB utilized, minimizing software costs.
Personal Computer Hardware	0	Used personal laptop with sufficient processing capabilities (Intel i5, 8GB RAM).
Dataset Acquisition	0	Utilized publicly available cancer imaging archives and databases (TCIA, BraTS).
Image Preprocessing Tools	0	Employed built-in MATLAB functions and open-source toolkits.
Miscellaneous (Electricity, Internet)	1000	Estimated utility costs, including internet and power consumption during development.
Documentation and Printing	200	Costs for project report printing and presentation materials.
Total	1200	Efficiently managed cost by leveraging free resources and academic tools.

Analysis:

The project was designed with a focus on cost-efficiency, utilizing publicly available datasets and academic software licenses. The primary investment was time and effort, as well as operational costs like electricity and internet. The minimal cost highlights the feasibility of developing similar projects in academic settings with limited funding.

10. PROJECT OUTCOME

The outcome of this project is a comprehensive, MATLAB-based system that automates the detection and classification of brain tumours using MRI scans. The project achieved the following milestones:

1. **Segmentation Techniques:**

- Successfully applied and compared multiple segmentation methods (Otsu, Canny, Watershed, Fuzzy C-means, K-means) to extract tumour regions.
- Enhanced segmentation accuracy through preprocessing with anisotropic diffusion filtering.

2. **Feature Extraction:**

- Employed advanced feature extraction techniques, including Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Gray-Level Co-occurrence Matrix (GLCM), providing robust and comprehensive feature representation.

3. **Classification Models:**

- Integrated state-of-the-art deep learning classifiers (ResNet-50, Inception V3) alongside traditional machine learning (SVM), achieving high classification accuracy across tumour types (glioma, melanoma, pituitary tumour, and no tumour).
- Demonstrated the effectiveness of combining deep learning with traditional segmentation techniques for improved performance.

4. **User-Friendly GUI:**

- Developed a graphical user interface (GUI) for streamlined user interaction, allowing healthcare professionals to easily load MRI images, preprocess, segment, and classify the tumour type with a single click.

5. **Impact and Usability:**

- The tool provides an efficient, non-invasive diagnostic aid, potentially improving early detection rates and assisting in treatment planning for patients with brain tumours.
- The project lays the foundation for future enhancements, such as real-time processing and integration with hospital imaging systems.

11. PUBLICATION/PATENT

The innovative combination of segmentation, feature extraction, and classification techniques makes this project a strong candidate for publication and potential patent filing. Venues for publication include:

- **IEEE Transactions on Medical Imaging:** A top-tier journal known for publishing innovative research in medical image processing and analysis.
- **Journal of Medical Imaging and Health Informatics:** Offers visibility within the medical imaging research community.
- **Computerized Medical Imaging and Graphics:** Focuses on novel methods for computer-aided diagnosis, making it an ideal fit for this project.

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