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Brain Tumor Dectection

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Abstract:
Due to the high risk of incorrect prediction and diagnosis associated with human-assisted manual categorization, brain tumor segmentation ranks high among the most important and challenging challenges in the field of medical image processing. It becomes an even more tedious ordeal when dealing with a mountain of data. Because brain tumors may seem quite different from one another and because tumors and normal tissues are so similar, it can be very difficult to remove tumor areas from pictures. This research presents a strategy for tumour extraction from 2D MRI scans using a Fuzzy C-Means clustering algorithm, conventional classifiers, and a convolutional neural network. Various tumor sizes, locations, forms, and picture intensities were accounted for in the real-time dataset used in the experimental investigation. Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes, and Random Forest were the six classic classifiers used in the traditional classifier component of scikit-learn. Convolutional Neural Networks (CNNs) built using Keras and Tensorflow were the next step as they outperformed the older, more conventional methods. The 97.87% accuracy that CNN achieved in our study is quite impressive. The primary objective of this research is to use statistical and texture-based information to differentiate between typical and out-of-the-ordinary pixels.

Keywords: K-Nearest Neighbor, Support Vector Machine, Multilayer Perceptron, Convolutional Neural Network

I. INTRODUCTION

In medicine, "medical imaging" may mean a variety of non-invasive ways to view into a patient's body. When it comes to improving people's health, medical imaging which uses a diagnostic and therapeutic representations of the human body created using a variety of imaging modalities and processes is paramount and decisive. One of the most important steps in image processing, imageAmong the many crucial stages in picture processing segmentation, determines how well subsequent levels of processing work. When it comes to medical image processing, picture segmentation is all about finding tumors or lesions, making machine vision work better, and getting good results for subsequent diagnoses. With the use of CAD systems, enhancing the medical imaging has become increasingly challenging as it concerns the sensitivity and specificity of cancer or lesion detection. Over 190,000 individuals worldwide get a diagnosis of primary or metastatic brain (secondary) cancers each year. There are several commonalities among brain tumor patients, even if their exact causes remain unknown. Anyone may be affected by it, regardless of age. At first, the tumor location was shown to have a lower risk of death. Consequently, imaging studies of brain tumors have become more prominent in the radiology department. Although several investigations have sought to identify brain tumor causes, no definitive findings have been reached. Using the k-means clustering approach in conjunction with the FCM methodology, an effective partitioning strategy was shown. this method will get a k-indicates that clustering according to the minimal computation time for FCM helps in improving accuracy. For the first evaluation of brain tumors, Amato et al. organized PCassisted recognition with mathematical morphological reconstruction (MMR). The results of the tests demonstrate that the segmented pictures are quite accurate and that the computation time is significantly reduced.

In order to better identify brain tumors, a new classifier system was created. The accuracy rate of the suggested system was 92.31%. An advanced machine learning strategy and brain structure analytics were proposed as a means of categorizing the MRI pictures of the brain in. This method offers better accuracy in identifying the divided brain regions and in determining the ROI of the afflicted area. A researcher in presented a hybrid approach for sectioning brain MR images that incorporated DWT transform for feature extraction, a genetic algorithm to reduce the number of features, and vector machine classification (SVM).One way to evaluate signals or images is by converting them to Berkeley wavelets (BWTs), which are defined as transformations of two-dimensional triadic wavelets. Spatial location, band pass frequency, quadrature phase, band pass orientation tuning, and other characteristics make use of the BWT. The BWT technique enables a smooth transfer from one spatial form to a temporal domain frequency, much as the mother wavelet conversion or other wavelet transformation communities. Being a fully orthonormal approach, the BWT is a significant tool for transforming images. Eight primary mother wavelets are paired together in BWT, with each pair having a unique angle of 0, 45, 90, or 135 degrees. A wavelet with odd symmetry and a symmetrical wavelet are both included within a pair of wavelet transformations. In order to save computing power, the BWT technique is helpful as it provides an exact orthonormal foundation. For effective division, the Berkeley wavelet transform is used here. When compared to other signal analysis methods, wavelet analysis is more efficient and may disclose data characteristics.

Brain tumors are characterized by aberrant cells in the brain. Malignant or benign tumors are both possible. An aggressive and fast-growing brain tumor invades neighboring tissues when it proceeds to a malignant state. It has the potential to metastasize, or move to other regions of the brain, and impact the CNS. Tumors that begin in the brain are called primary tumors, while tumors that have traveled from other parts of the body to the brain are called brain metastatic tumors. In contrast, benign brain tumors have a slow development inside the brain. Consequently, there are more treatment options and a higher chance of survival may be achieved by early identification of brain tumors. However, due to the high volume of MRI images produced in the course of medical practice, manual segmentation of tumors or lesions is an arduous, difficult, and time-consuming process. Brain tumors and other lesions are the most common targets of Magnetic Resonance Imaging (MRI). Medical image processing requires the segmentation of brain tumors from magnetic resonance imaging (MRI) due to the large amount of data often involved. Moreover, soft tissue may surround the tumors' borders. In spite of this, it is very difficult to accurately segment tumors from human brain tissue.

II. LITERATURE SURVEY

1.“Devkota et al. established the whole segmentation process based on Mathematical morphological operations and the spatial FCM algorithm”, which reducing computation time, but not yet evaluated. So far, it has shown promising results, such as a 92% cancer detection rate and an 86.6% classifier accuracy. Similar to a histogram-based segmentation method, Yantao et al. Considering the goal of brain tumor segmentation as a three-category system (tumor, edema, and normal),.

2.“B Shivhare, Sharma and Singh presented a fully automated strategy”. In addition to using K-means clustering algorithms, morphological operations such as dilation and hole filling are incorporated.

As compared with the ground truth, the Dice Similarity Coefficient (DSC) of 75% was obtained based on the Brats 2015 training dataset.

3.“Jagan [13] presented a novel approach for segmentation of tumor”. The first step in segmentation is using the FCM method and the enhanced Expectation Maximization (EM) method. Afterwards, the proposed method is used to conduct superior segmentation. The proposed method's performance in terms of segmentation accuracy is compared to that of the FCM clustering method and the upgraded EM method. After calculating segmentation accuracy for 10 patients, the suggested technique beat both the FCM clustering and enhanced EM approaches, with an average result of 97.98%.

4. “Filho et al. [14] presented an Optimum Path Snakes (OPS)”. The characteristics, such texture, are first extracted during pre-processing utilizing tools like HU moments, GLCM, HDA, and statistical moments. After that, the OPS approach is used for segmentation. A measure of performance that is often used is the Hausdorff distance (HD).

5.“Dandu et al. [15] presented a Statistical Region Merging (SRM) and Back Propagation Neural Network (BPNN)” using Statistical Region Merging (SRM) and Back Propagation Neural Networks (BPNN). Decision Based Couple Window Median Filter (DBCWMF) preprocessing is the first step in this procedure. The next step is to apply SRM for segmentation. After that, methods like Scale Invariant Feature Transform (SIFT) and Cat Swarm Optimization (CSO) are used to extract features. To classify the data, BPNN classifier is used. The suggested method ranks DBCWMF higher than the median and PGPD filter, and the BPNN classifier higher than the ANN and AdaBoost classifiers. Using measures for accuracy, precision, specificity, recall, and peak signal-to-noise ratio (PSNR), the proposed technique exceeds the state-of-the-art methods.

6. “Suneetha and Rani [16] suggested a nove1 technique for detection of brain tumor in early stages”. Optimized Kernel Possibilistic C-means Method (OKPCM) pre-processing of obtained brain MRI images is the suggested procedure. After that, an adaptive Double Window Modified Trimmed Mean Filter (DWMTMF) is used to improve the picture. Lastly, the region expanding approach is used to do picture segmentation. In terms of processing time and accuracy, the proposed OKPCM method is compared to K-means, CLOPE, and FCM methods. When compared to previous approaches, the suggested OKPCM yields superior accuracy. The K-means algorithm, however, is quicker when considering processing time. We evaluate the suggested DW-MTMF filter against the median, mean, and BM3D filters using MSE and PSNR metrics. Among the filters, DW-MTMF outperforms the others. Accuracy and error rate metrics are used to compare the suggested region expanding segmentation approach against k-Nearest Neighbors (k-NN), edge detection, and fuzzy algorithms. All other strategies are surpassed by the region growth strategy.

7.“Deepa and Emmanuel [19] presented a fused feature Adaptive Firefly Backpropagation Neural Network (AFBNN)” approach for brain tumor detection A first step in image processing is applying an average filter to the raw picture. After that, the Gabor Wavelet method is used to extract the geographical, directional, and frequency-based texture information. Then, Kernel Principle Component Analysis (KPCA) is used to choose the most important characteristics. Important details are supplied by fusing features using the GRBF (Gaussian Radial Basis Function). At last, the AFBNN classifier is used for classification. Using the BRATS 2015 dataset, the suggested method is confirmed to work. Using sensitivity, accuracy, and specificity as performance indicators, the suggested method is tested against the Naïve Bayes, SVM, and Linear Discriminate Analysis (LDA) classifiers. When compared to other classifiers, the suggested method is superior.

8.“Lim and Mandava presented a multi-phase technique for segmenting the multisequence image of brain tumor”. There are three steps to the method that has been suggested. At the beginning, the data is modeled using the random wa1ks approach. The second step is to employ a weighted average method to fuse the data. Information Theoretic Rough Sets (ITRS) are used in the final step for the extraction of visual objects. In order to evaluate the technique, the MICCAI brain tumor dataset is used. There is a relationship between the proposed method and the PCA fusion and simple averaging approaches. According to the results of the DICE measure, which was used to assess the effectiveness of the proposed approach, the average DICE accuracy for high grade tumors was 0.7 while for low grade tumors it was 0.63.

9.“K, T and S presented an efficient approach for detection of brain tumor”. Linear Expansion of Thresholds (PURE-LET) transform is first used to denoize the recorded MRI image. After that, a method that combines the MultiTexton Microstructure Descriptor (MTMD) with the Modified Multi-Texton Histogram (MMTH) is used to extract the features. The next step is to compare the results using a hybrid of two more feature extraction methods, namely GLRLM and GLCM. The last step in picture classification is training classifiers like kNN, SVM, and Extreme Learning Machine (ELM) using the features that were retrieved earlier. By evaluating the performance of three classifiers according to the proposed method, the sensitivity, specificity, and accuracy of the results are correlated. An accuracy of 80% is achieved by the proposed technique with kNN; 95% is achieved with SVM; and 91% with ELM.The suggested method using the SVM classifier outperforms the other two classifiers in terms of accuracy.

10.“Nanda et al. presented a hybrid K-means Galactic Swarm Optimization (GSO)” For determining the size, shape, and location of brain tumors, Otsu's entropy is used as a fitness function. In comparison with existing methods, the proposed method compares computational time, NRMSE, SSIM, PSNR, and K-means.It is better than state-of-the-art methods on every performance metric except computational time. In comparison to current methods, the proposed methodology has a higher computing cost.

11.“Vishnuvarthanan et al. [23] presented an automated method for segmenting the tumor and tissues” which is based on thet techniques for clustering and optimizing data. MRI images of skull-stripped brains are used as inputs for this technique. A contrast restricted adaptive histogram equalization approach is used to prepare the skull picture for further processing. The MFKM approach is used to cluster the data. A Bacteria Foraging Optimization (BFO) code is used to find the best threshold value. Based on the established cutoff, the MFKM method's output is re-evaluated. The suggested method is linked to both traditional FCM methods and those based on Particle Swarm Optimization (PSO), as well as the current MFKM method. Storage need, computing time, sensitivity, Jaccard Index (JI), specificity, and MSE are some of the performance measures used to evaluate the proposed technique.

12.“Sompong and Wongthanavasu [24] presented a segmentation technique” An improved tumor cutting technique is used, which utilizes cellular automata. By using GLCM-CA, a picture can be converted into the desired feature image.The next step is to use the enhanced tumor cut approach to do the segmentation. Using BraTS 2013 as a dataset, the proposed technique was evaluated on DC, sensitivity, specificity, and PPV. A comparison is made between the suggested approach and state-of-the-art approaches that make use of the same dataset. The suggested technique outperforms the current best practices when compared side by side.

13.“Zhang et al. [26] presented a Multilayer Perceptron (MLP) approach for detection of pathological brain”. The first stage involves extracting 12 features using Fractional Fourier Entropy (FRFE). The next stage is classifying the data using an MLP classifier. The optimal amount of hidden neurons is found by using a pruning method. According to the data, the average accuracy was 99.53% when FRFE, KC, MLP, and ARCBBO were combined. The suggested method beats out two existing classifiers, a support vector machine (SVM) and a native Bayesian classifier.

II. RELATED WORKS

A. Problem Analysis

Existing System

Using image processing techniques, the current system was able to detect brain cancer. To begin, a CT scan of the brain is obtained and subjected to the pre-processing procedures. Segmentation of the pre-processed picture follows. Brain cancer detection methods in these systems were limited to segmentation. These methods also have their flaws, but they can be ironed out with better technology. Additionally, no one has determined to what stage the disease belongs; all they have done is determine whether it is malignant or not.

Disadvantages

- Limitations on segmentation are a limitation of many systems.
- Some technological problems plague them.
- Only images of cancer can be processed by certain systems.
- There has been no staging.
- Reduced precision.
- The tumor's area is not calculated.

Proposed System

Three diagnostic tasks—pre-processing, segmentation, and feature extraction—make up the suggested strategy for identifying a brain tumor. We will use this information to determine and categorize the region at a later time. Preprocessing is performed on the acquired CT image, as previously stated. We extract characteristics from the segmented preprocessed picture after it has been segmented. At last, we use the characteristics that were extracted to categorize the picture. Part one of this experiment outlined our intended outcomes; part two focused on determining whether or not the supplied magnetic resonance imaging (MRI) scans showed the existence of a brain tumor. Tumor categorization is found in the other section, the second portion. Typically, this is the process flow diagram. Improving the image data in a way that strengthens the picture attributes that are crucial for further processing is the goal of preprocessing. Digital images may be used in subsequent processes by splitting them into several parts, a technique called image segmentation.

Open Problems In Existing System

1. MRI images of the brain :

According to the plan, this is the first stage. The quality of the generated MRI pictures can be inadequate for analysis. Visuals could lack sharpness, contrast, and noise. It may be challenging to extract the region of interest [14]. The system is fed grayscale MRI pictures in this case.

2. Pre-Processing :

Data preparation for primary processing or further analysis begins at this stage of processing. The activities typically required prior to the target analysis, data extraction, and geometric modifications of the original picture are mostly included in the preprocessing phase of our project. Some examples of these enhancements include smoothing out data that is too jagged or has too much noise, eliminating data that represents an element that isn't part of the brain, and adjusting the data so that it accurately represents the original picture. Getting this raw MRI picture into a usable format is the first step in preprocessing.

3. Feature Extraction :

It is the method by which certain visual characteristics are identified and made available for further analysis. The majority of image and computer vision solutions rely on this. The tumor is categorized according to the findings from the sign extraction process. Size, shape, composition, and image placement are some of the characteristics considered during extraction. In this stage, the input image's features are extracted. These features allow for the analysis of the picture and the localization of the tumor. The MRI picture generated before feature extraction is shown in Figure 2 below.

4. Segmentation :

The process of segmentation involves dividing a picture into smaller and smaller sections. Carried out in order to make analysis simpler. To segment an image for the sake of this project is to divide it into several smaller pictures; nevertheless, the degree of the image is the primary determinant of the difficulty of segmentation, and unlike X-ray film or magnetic resonance imaging (MRI), images are not inherited in a continuous region. Each action's location is referred to as an element in 2D individual pictures and a voxel in 3D images.

III. METHODOLOGY

Methods for picture Segmentation Image segmentation involves dividing a picture into homogeneous, highly-specific regions that adhere to a set of established criteria. Differentiating between the brain's normal and pathological tissues is what segmentation is all about when it comes to brain tumors.

Segmentation techniques are generally divided into the following categories:

- Thresholding techniques
- Region growing techniques
- Edge based techniques
- Clustering techniques
- Watershed technique
- Deformable model-based techniques.

Thresholding Techniques

Thresholding is a widely used segmentation approach. The picture is split into two groups based on the threshold value; one group contains pixels with values higher than or equal to the threshold, while the other group contains pixels with values lower than the threshold. There are three distinct kinds of thresholding methods: adaptive, global, and local. In local thresholding, the threshold value is determined by using local attributes, such the standard deviation or local mean value, of different picture areas. Using the picture's histogram, a single threshold value is chosen for the whole image in global thresholding. Local threshold values are selected separately for every pixel in adaptive or dynamic thresholding. The threshold value has a significant impact on the segmentation outcome. Choosing the wrong threshold value leads to inaccurate segmentation. A number of approaches, including Otsu's thresholding, have been put forth to automate the threshold selection process. Thresholding methods are sensitive to noise because they ignore the image's spatial features.

Region Growing Techniques:

The pictures are divided using the closest pixel of a comparable sort (homogeneity, texture, intensity levels, and sharpness) in the area growing segmentation approach. The procedure starts off by picking a starting seed point according to established rules. So, we gradually add the nearby pixels to the seed based on homogeneity requirements. The method is easy to understand and use, and it successfully creates big areas out of picture pixels that have comparable characteristics. This method outperforms the histogram thresholding strategy in terms of segmentation and is less affected by noise as it considers the spatial features of the picture. This method accurately segments areas that are geographically isolated or have comparable characteristics. This method also produces linked areas. The most significant drawback of this method is that it has the potential to produce unconnected areas and holes in the determined form.

Edge Based Techniques:

The intensity gradient of a certain pixel or cluster of pixels is what defines an image's border or edge [6]. The pixels in a picture that correspond to the visible object's edges are located using edge-based approaches. The result is a binary picture that includes the pixels at the edges. Various edge operators, including Laplacian, Sobel, Canny, Prewitt, etc., are used in this method. For straightforward, noise-free pictures, edge-based methods work well. These methods may introduce additional or missing edges to the noisy pictures [8]. These methods don't need any previous knowledge about the image's content and are computationally quick. The primary issue with these methods is that the object's edges do not completely encapsulate it [6]. The inability to get the desired results in environments with a lot of background noise is another drawback of these methods.

Flow Chart

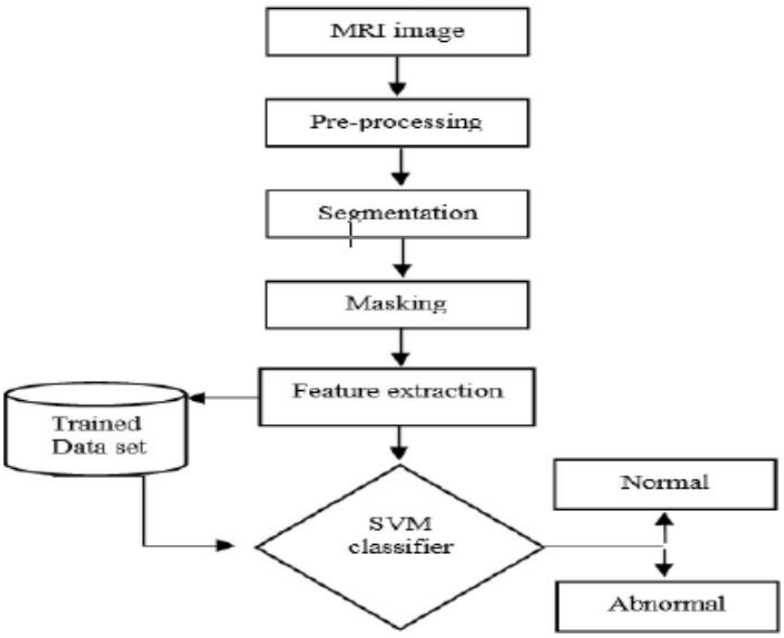

Fig.1. Brain tumor detection steps.

Architecture Of Proposed System

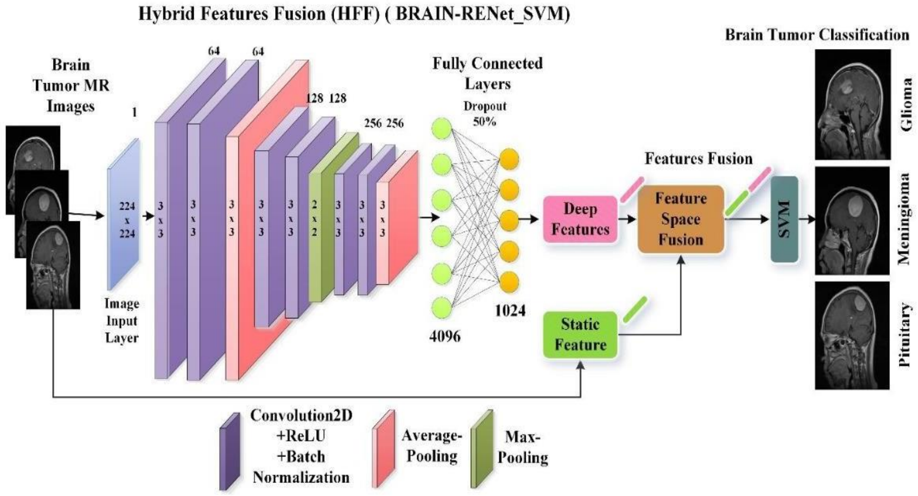

Fig.2. The proposed BRAIN-RENet deep CNN for

Brain Tumor Classification

To begin, this study compiles a database of all available images; next, it uses a genetic algorithm to narrow down the characteristics to those that are most relevant for supporting the SVM-based categorization of brain tumors. Figure depicts the procedure for diagnosing brain tumors. Ultimately, the picture is successfully classified by the SVM Naćve Bayes, BOV-based SVM classifier, and CNN.

Segmentation using FCM: For this segmentation, we used the Fuzzy C-Means clustering approach, which permits a single data point to be a member of many clusters. At this point, we obtained the fuzzy clustered segmented picture, which guaranteed improved segmentation.

Morphological Operation: Here is the morphological operation: we require just the brain part, not the skull component, to segment the tumor. This was accomplished by implementing morphological procedures on our photos. Erosion was first used to demarcate MRI areas with poor connections. As a result of erosion, our photos will display several separate areas. The next step was to apply dilation.

Tumor Contouring: A thresholding-based intensity-based method was used for tumor cluster extraction. The result of this picture is a black-and-white image of the tumor region.

Feature Extaction: Two kinds of characteristics were retrieved for use in the categorization process. The segmented MRI images were used to extract features based on texture (Dissimilarity, Homogeneity, Energy, Correlation, ASM) and statistics (Mean, Entropy, Centroid, Standard Deviation, Skewness, Kurtosis).

Raditional Classifiers: For our suggested model's tumor identification accuracy, we used six classic machine learning classifiers: K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Naïve Bayes, Random Forest, and Support Vector Machine.

Evaluation Stage: In the evaluation stage, we compare our suggested segmentation strategy to various region-based techniques. Our model successfully divides the ROI and separates the tumor component.

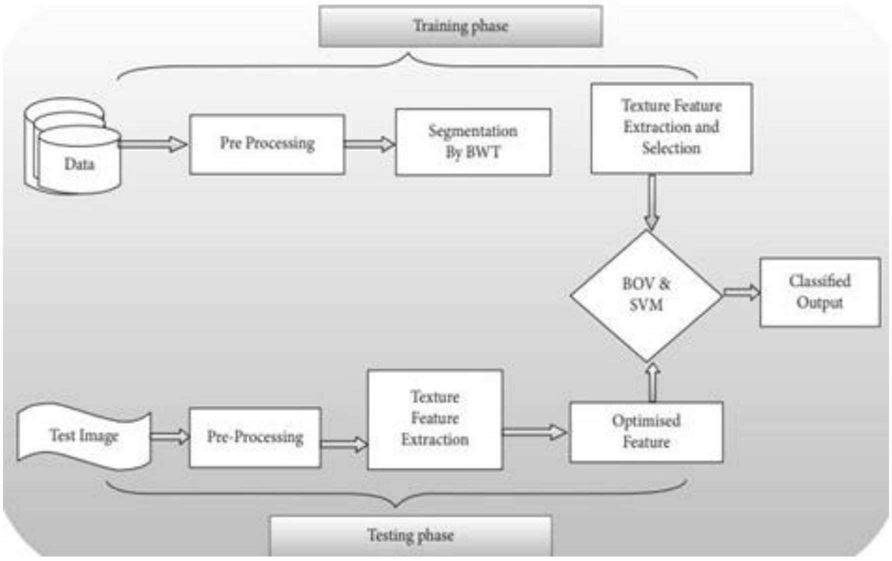

Fig.3. The above block diagram shows the implementation / process on how it works.

Skull Stripping: Because the MRI picture's backdrop doesn't carry any valuable information and only adds processing time, an essential part of processing medical images is removing the skull. Our process included three stages of removing the skull from the MRI scans. These three procedures are:

1. ***Otsu Thresholding:*** The first efforts at removing the skull used Otsu's Thresholding method, which automatically finds the threshold value and separates the image into foreground and background components. By reducing the intra-class variance—the weighted average of the dispersion of the two classes—this approach identifies the appropriate threshold.
2. ***Connected Component Analysis:*** The last step was to isolate the brain region using linked component analysis, which allowed us to eliminate the skull portion of the skull stripping process.
3. ***Filtering and Enhancement:*** Improving segmentation requires optimizing MRI image quality while limiting noise, because brain MRI photos are the most noise-prone of all medical imaging. In our study, we used a Gaussian blur filter to reduce the inherent Gaussian noise in brain MRI, which significantly improved the segmentation performance.

Working Flow Devised for Proposed Methodology

1. Load the input dataset
2. Adding a Convolution Layer with 32 convolutional filter
3. Passing the Convolutional kernel into the Max Pooling layer
4. Pooled feature map is used to get the single column vector
5. Processing of the vector in dense layer with 128 nodes
6. Final dense layer applying Sigmoid as the Activation function
7. Validation stage and Performance evaluation

Fig.4. Workflow devised for proposed Methodology

IV. RESULTS AND IDSCUSSION

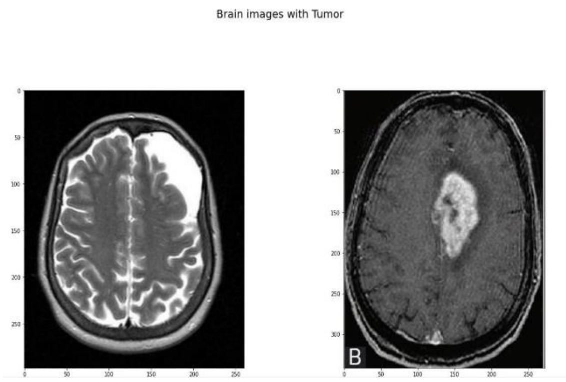

Fig.5. Brain images with no Tumor

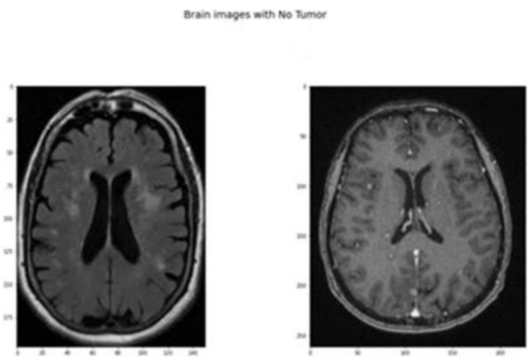

Fig.6. Brain images with Tumor

We get an admirable outcome for tumor identification using the five-layer methods that was suggested. The suggested five-layer convolutional neural network (CNN) model includes two dense layers, flatten, max pooling, and convolution. Since CNN is translation invariant, data augmentation was performed prior to model fitting. By dividing the dataset in half, we may assess the performance in two different ways. Using a 70:30 split and a training accuracy of 99.01%, we get a 92.98% success rate. We reached a 97.87% accuracy rate and a 98.47% training accuracy rate in the second iteration, with 80% of the photos trained and the remaining images tested. In this case, an 80:20 split is optimal for our suggested model. The results of the suggested CNN-based approach are shown in Table-IV. Using five-layer CNN, we achieved an impressive accuracy of 97.87%. We tried a few other CNN models with varying numbers of layers, but the results were pretty similar when we stuck with our five-layer setup. We saw an enormous rise in calculation time, method complexity, batch size, and steps per as the number of layers increased. Additionally, the accuracy flattened, thus we did not compensate the model with 0.2 as the dropout amount. That is why, without resorting to dropout, our model delivers the highest level of accuracy.

V. CONCLUSION

To conclude, early diagnosis of brain tumors is paramount to effective treatment. Here, we suggest a novel two-stage paradigm for detecting and classifying brain tumors, which should enhance diagnostic accuracy while decreasing computing complexity. Our DBFS-EC approach is proposed for detecting brain tumors with fewer false negatives than existing DL techniques, and its performance is evaluated. It has been demonstrated that the proposed DBFS-EC works.

VI. FUTURE WORK

Future advancements in medical image processing, such as the ability to identify brain tumors in a timely manner for accurate diagnosis, are the primary emphasis of this paper. It is not possible to tell whether the segmented area is normal or pathological using current methods that use pre-processing and segmentation stages to identify brain tumors. Previous research has used feature extraction and classification, among other steps, to somewhat accurately categorize the extracted area as normal or abnormal. Modeling improved techniques for automating the work of identifying brain tumors will be continued in this assignment, with the goal of producing better outcomes than current systems.

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