Improving Brain Tumor Segmentation in MRI Images through Enhanced Convolutional Neural Networks

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***Abstract*—Achieving precise tumor segmentation is essential for accurate diagnosis. Since brain tumors segmentation require a significant training process, reducing the training time is critical for timely treatment. The research focuses on enhancing brain tumor segmentation in MRI images by using Convolutional Neural Networks and reducing training time by using MATLAB's GoogLeNet, anisotropic diffusion filtering, morphological operation, and sector vector machine for MRI images. The proposed method will allow for efficient analysis and management of enormous amounts of MRI image data, the earliest practicable early diagnosis, and assistance in the classification of normal, benign, or malignant patient cases. The SVM Classifier is used to find a cluster of tumors development in an MR slice, identify tumor cells, and assess the size of the tumor that appears to be present in order to diagnose brain tumors. The proposed method is evaluated using a dataset from Figshare that includes coronal, sagittal, and axial views of images taken with a T1-CE MRI modality. The accuracy of 2D tumor detection and segmentation are increased, enabling more 3D detection, and achieving a mean classification accuracy of 98% across system records. Finally, a hybrid approach of GoogLeNet deep learning algorithm and Convolution Neural Network- Support Vector Machines (CNN-SVM) deep learning is performed to increase the accuracy of tumor classification. The evaluations show that the proposed technique is significantly more effective than those currently in use. In the future, enhancement of the segmentation using artificial neural networks will help in the earlier and more precise detection of brain tumors. Early detection of brain tumors can benefit patients, healthcare providers, and the healthcare system as a whole. It can reduce healthcare costs associated with treating advanced stage tumors, and enables researchers to better understand the disease and develop more effective treatments.**

Keywords—MRI brain tumor; anisotropic; segmentation; SVM classifier; convolutional neural network

I. Introduction

All essential biological systems are controlled by the central nervous system (CNS), which is composed of the brain and spinal column which are the most important organs in our bodies' systems. The functions include speaking, moving, and thinking. They are made up of supporting cells called glial cells and nerve cells called neurons, which communicate with one another and with the rest of our body by both sending and receiving impulses via nerves. Magnetic resonance imaging (MRI), a category of imaging technology, provides accurate images of the anatomical anatomy of the human body, especially the brain, and provides useful data for biomedical research and clinical diagnosis. A brain tumor is the growth of malignant, abnormal cells in the brain [1]. There are numerous varieties of brain tumors and these tumors may be malignant (cancerous) or benign (noncancerous). Cancer may begin in any other parts of the body before spreading to the brain or it may begin there (primary brain tumors) (secondary, or metastatic, brain tumors). The rate of growth of a brain tumor might vary greatly. A brain tumor will have an effect on how well your nervous system functions based on how quickly it develops and where it is. Your treatment options are influenced by the type of brain tumor you have as well as its size and location. A learning model for the classification of lung and pancreatic tumors was introduced [2] where a knowledge transfer served as the foundation for the learning model's 3D CNN architecture. The stated accuracy metrics of the transfer learning-based algorithms were superior to those attained by manually developed techniques. Applications specifically connected to neuro-oncology have increased interest in transfer learning. Deep data from brain MRI images have been extracted in research using trained networks. Transfer learning may be used to work with smaller datasets, as illustrated by studies that applied AlexNet and GoogLeNet to grade gliomas from MRI scans [1]. In terms of efficiency metrics, GoogLeNet performed better than AlexNet, where GoogLeNet's work on classifying brain anomalies used deep transfer learning and obtained impressive classification performance [2]. Wavelet transform (WT) [3] is an important strategy for feature extraction from MR brain images, but it necessitates a substantial amount of storage and is computationally expensive. Wavelet transform (WT) allows analysis of images at various levels of resolution due to its multiple-resolution analytic property [4]. Principal component analysis is appealing because it observe the impact the dimensionality of data and lowers the computational cost of processing new data [5]. The supervised classifier shows better performance than the unsupervised classifier in terms of classification success rates, regardless of the fact that all of these strategies led to successful outcomes. The classification accuracy of the preponderance of previous methods was less than 95%, therefore the purpose of the proposed research is to find a method that is significantly accurate. A CNN-based deep learning model was successfully used to solve the classification task for brain tumors. CNN-based classifier systems give a completely automated classifier that doesn't required manually segmented tumor regions, which is a benefit. For the purpose of identifying traits from brain MRI, a CNN architecture was introduced [6] where the effectiveness of the algorithm was enhanced by using CNN features and a classifier model from the category of extreme learning machines (ELM). Recall measures for the class meningioma were somewhat low for this trial; however they were quite high for the class pituitary tumor. It illustrates that there are boundaries on the classifier's ability to discriminate. SVMs, which are state-of-the-art supervised classification methods based on machine learning theory, are currently used in many applications. Due to their extreme precision, exquisite mathematical tractability, and simple geometric interpretation, SVMs outperform existing methodologies like artificial neural networks, decision trees, and Bayesian networks by a massive margin [7]. Manual segmentation of brain tumors that is usually very challenging and time-consuming is frequently done by experts.

The remaining part of the paper is organized as follows: Section II the related works to the proposed approach. Section III describes the dataset use magnetic resonance brain image and the classifier settings which include the anisotropic filtering, support vector machine filtering, deep classification neutral network feature and deep convolutional neutral is network. Section IV gives details of the experiment performed presents evaluation results and provides discussion on the results. Section V provides the conclusion of the study.

II. Related Works

The feature extraction approach uses a Stationary Wavelet Packet Transform (SWPT)[6]. The best feature is then selected by implementing a hybrid of adaptive black widow and moth flame optimisation (HABWMFO). The feature values undergo clustering in order to perform segmentation. For segmentation, the Adaptive Kernel Fuzzy C Means clustering technique (AKFCM) was developed. Finally, and certainly not least, the Dolphin-SCA deep learning method, which is based on deep CNN, implemented the Hybrid Convolution Neural Network-Long Short-Term Memory (CNN-LSTM) component to improve the accuracy of tumor classification.[7]. It helps with accuracy and enables efficient classification selections. Dolphin-SCA (Dolphin Echolocation based Sine Cosine Algorithm), along with the fuzzy deformable fusion model, were used to segment the data. The features were extracted using Power LDP and statistical traits (skewness, mean, and variance). The information was used to classify brain tumors using the Deep Convolution Neural Network, which trains using Dolphin-SCA. Brain tumors are segmented using a hybrid k-means algorithm and the fuzzy c-means technique [8]. For automatically identifying brain tumor cells in MRI MRI images, a deep CNN model has been created. On synthetic and real-time datasets, it has been tested [9]. Using the GoogleNet and AlexNet architecture, the CNN network is trained on the training dataset, and the performance of the data model is assessed on the test dataset. The model's performance is evaluated using the metrics accuracy, sensitivity, specificity, and AUC integrating an implemented extreme learning machine with a hybrid feature extraction technique [10]. Using the RELM (regularised extreme learning machine), the tumor kind was classified. A Deep Wavelet Auto-encoder (DWA), which combines the auto-encoder, a fundamental feature reduction property, and the wavelet transform, an image decomposition method, is used for picture reduction [11]. A brain imaging dataset was produced using a DWA-DNN image classifier. A CNN-based U-net [12] for segmenting the tumor has been introduced where the transfer learning is based on a Vgg16 pre-trained convolutional foundation. To grade the tumor, a fully connected classifier was utilized.

III. Materials and Method

In the proposed approach, a novel upgraded classification model is proposed in an attempt to enhance tumor segmentation performance. Enhanced Convolutional Neural Networks are used to segment brain tumors. Automatic segmentation is carried out using the BAT algorithm, which strips the skull from the MRI image before applying the loss function to preprocess it. Deeper architectures are built utilising smaller kernels. Despite decreasing the probability of computational complexity given a network includes fewer weights [13].

The proposed methodology incorporated anistropic diffusion, morphological operation, and SVM segmentation. On the figshare open dataset, the suggested approach had the best classification performance. Combining transfer learned deep CNN features and SVM classifier models improve performance. The combination excels even with less training samples utilised in the original input space on the dataset conducted in MATLAB, achieving the highest classification accuracy. The dataset comprises of 3064 brain MRI images taken from 233 patients who have been diagnosed with one of the three forms of brain tumors, which are meningioma, glioma, or pituitary tumors. The T1-CE MRI modality includes the axial, sagittal, and coronal images. It includes 1426 brain MRI images with glioma (corresponding to 89 patients), 708 meningioma photos (related to 82 patients), and the remaining 930 pituitary tumor images (belonging to 62 patients). Each image is 512x512 pixels in size and is accessible mat files. The input layer for Google Net's original RGB colour image design was 224x224x3. In the proposed approach, which aims to segment tumor using MRI images, automatic classification has been performed under Anisotropic Diffusion as tumor found and no tumor found. CNN, a successful deep learning method, was used as a classifier within the scope of the study. CNN architectures were used GoogLeNet. The classification results were obtained using the original MRI brain images, and the images obtained by using SVM. Then, new classification results were calculated using a framework from the obtained results.

A. Anisotropic Diffusion Filter

In order to perform morphological operations on the MRI image and determine if the patient's brain contains a tumor or not, the picture was first filtered using an anisotropic diffusion filter to lessen contrast between adjacent pixels. The image was then manually turned to black and white using a threshold value after being scaled. It is the first step in identifying potential tumor locations [14]. Morphological techniques have been used on the semi-processed image to acquire data on the areas and solidity of the likely places. The statistical average of many MRI pictures with tumor has been used to calculate the minimal value of both of these characters. The final detection result was then delivered using it [15]. Although the majority of the time the simulation technique can produce accurate results, it cannot function when the tumor is hollow or too small. getting an MRI scan, using an anisotropic diffusion filter to filter the image, processing the image with morphological operations in detail, the tumor is divided up by a specific border, if there is no tumor, image processing is finished; otherwise, the tumor's location is estimated. Tumor identification is based on density and size [16]. Each parameterized image that results from shape-adapted smoothing is a combination of the original image and a filter that depends on the local content of the original image. As a result, anisotropic diffusion transforms the original image in a non-linear and space-variant way. The photos are blurred with the anisotropic filter without losing any edges.

$$\frac{\partial I}{\partial t} = div\,(c(x, y, t), \nabla I) = \nabla c.\nabla I \quad (1)$$

where the diffusion coefficient is denoted by c (x, y, t). It is chosen to maintain image edges and regulates the rate of diffusion. The ground-breaking Perona-Malik paper's projected diffusion co-efficient is as follows:

$$c\left(\left||\nabla I|\right|\right) = \exp\left(-\frac{||\nabla I||}{K}\right)^2 \; or \; c\left(\left||\nabla I|\right|\right) = \frac{1}{1+\left(\frac{||\nabla I||}{K}\right)^2} \quad (2)$$

B. Data Pre-Processing

Morphology is a technique for removing visual cues like boundaries and skeletons that aid in the legation and recital of region shapes. It works by enlarging things, filling gaps, and then connecting all the broken things. The size of the thing is also diminished. The erosion process in a binary image eliminates the foreground background pixels. The image is subjected to morphological opening after being converted into a binary image [17]. To segment out the tumor spot from the image, a Binary tumor masked window must be created. Noise removal occurs during the pre-processing step and can be accomplished using a variety of spatial filters, including linear and nonlinear filters (Median filter). After segmentation, morphological processing is used to remove undesirable parts, and other artefacts, such as text, are removed.

C. Morphological Operation

It entails image opening, image closing, dilation, erosion operations, and a conclusion has been made regarding whether or not there is a tumor present in the MRI picture and whether it is normal or pathological. It is also where the RGB to grey conversion and reshaping happens. It has a median filter to reduce noise. The likelihood of noise appearing during a modern MRI scan is extremely low. It might come as a result of heat influence. The images frequently employs the following elements: threshold, edge, pixels, cluster, and neural network [18]. The study of morphology focuses on form-based image processing. An output image of the same size is produced by adding a structural element to the previously processed input image. Every surrounding pixel is compared to every input pixel, and the comparison's findings are used to determine the values of the corresponding output pixels. Erosion and dilation are the two primary morphological processes. Pixels are either added to the boundaries of the objects during dilation or subtracted from them during erosion, depending on the size and shape of the structuring elements. When comparing, the dilation action gives the output the greatest value of the adjacent surrounding pixels, while the erosion operation gives the output the lowest value of the nearby surrounding pixels. There are various clustering techniques, including the mountain, K-means, fuzzy C-means, and subtractive approach. The most popular clustering method is called k-means clustering [19]. Compared to hierarchical clustering, it is more straightforward, speedier, and capable of handling a high number of variables.

The technique of segmenting an image into different parts or sections is known as picture segmentation. The main objective is to make the visual representation simpler or transform it into something else that is more straightforward and analytically insightful. It is employed to identify borders and objects in pictures. Every pixel in an image has a label assigned to it, and pixels with the same label have similar properties. Image classification is a well-known issue in image processing. The main objective of image classification is to foretell the categories of the input images using the features. Various classifiers exist, including ANNs (Artificial Neural Networks) and SVMs (Support Vector Machine). The segmentation stage is crucial for a thorough analysis of a picture because it determines how accurate the succeeding phases will be [20]. However, due to the wide variety of lesion shapes, sizes, and colours as well as various skin types and textures, effective segmentation is challenging. Additionally, some lesions have uneven borders, and occasionally, the border between the tumor and the skin is smooth. Many algorithms have been put up to solve the issue. Thresholding, edge-based or region-based, supervised and unsupervised classification approaches are some general categories that can be used to describe them. The normalisation intensity values for the MRI images in the dataset were likewise pre-processed [21].

```
%% Morphological Operation

label=bwlabel(sout);
stats=regionprops(logical(sout),'Solidity','Area','BoundingBox');
density=[stats.Solidity];
area=[stats.Area];
high_dense_area=density>0.6;
max_area=max(area(high_dense_area));
tumor_label=find(area==max_area);
tumor=ismember(label,tumor_label);

if max_area>100
   figure;
   imshow(tumor)
   title('tumor alone','FontSize',20);
else
    h = msgbox('No Tumor!!','status');
    %disp('no tumor');
    return;
end
```

Fig. 1. Morphological operation.

The intensity values between 0 and 1 were scaled using a min-max normalisation approach and resized to 224x224. The three channels were then produced by replicating the greyscale values three times because MRI pictures are greyscale images. A five-fold cross-validation at the patient level was followed by the evaluation of the created system using the Figshare dataset as shown in Fig. 1.

D. Convolutional Neural Network (CNN) for Tumor Classification in MRI Images

A deep neural network and deep learning architecture called a convolutional neural network (CNN) is applied by using transfer learning, where a deep neural network is utilized to both create new CNNs from scratch and to employ ones that already exist. The deep learning architecture is produced by combining sub-layers such as the convolution layer, activation function, pooling layer, flattening layer, and completely connected layer. The convolution layer is where the convolution procedure is carried out by segmenting the image[22]. On the other hand, activation functions are architectural elements that, depending on their function types, produce new outputs from their inputs. The layer on which pooling operations are carried out in order to reduce the larger image size caused by the convolution process is known as the pooling layer. Prior to entering the classification layer, the picture whose convolution procedures have been finished must be transformed from matrix to vector form. Feature matrices are converted into feature vectors by the process of flattening. [23][24]The classification procedure employing feature vectors and machine learning is the fully connected layer. One of the options, including support vector machines and artificial neural networks, might be chosen as machine learning.[3] Within the parameters of the study, brain tumors were segmented using transfer learning and a convolutional neural network. Feed-forward training of CNNs begins with the first input layer and continues to the final classification layer; following that, error back-propagation begins with the final classification layer and moves forward to the first convolutional layer. In a forward pass computed as follows, neuron j of layer l-1 provides input to neuron I in layer l.

$$\overline{\perp}\ n_i^l = \varepsilon_d^{\Pi} = 1^{w_{ij}^L \cdot xj+bi} \tag{3}$$

The output is computed by a nonlinearity ReLu function:

$$0ut_i^L = \max(0, In^l i\ ) \tag{4}$$

Equations (3) and (4) are used by all neurons in the convolutional and fully connected layers to calculate the input and provide an output in the form of nonlinear activation. The K-by-K square window sliding on the N-by-N feature map is used by the pooling layer, which uses the maximum or average value of the features inside the window. It produces a single value from the K K region, reducing the spatial dimension of the feature map from N N to N/K N/K. The Softmax function is used in the last layer to calculate the classification probability for each tumor type.

$$out_i^L = \frac{e_i n_i^L}{\varepsilon_i \in 0 \cup t_k^L} \tag{5}$$

By minimising the following cost function with regard to the unknown weights, back-propagation algorithms train ACNNs. X I is the ith sample in the training set with the label yi, and The training set's overall training sample count is indicated by m.

$$C = -\frac{1}{m}\Sigma_i^m \left(p\left(y^i \middle| X^i\right)\right) \tag{6}$$

E. Figshare Dataset of T1-CE MRI Modality MRI Images

The figshare dataset is freely accessible and frequently used to test classification and retrieval techniques. It consists of 3064 brain MRI pictures from 233 patients who have been identified as having one of the three types of brain tumors (meningioma, glioma, and pituitary tumors). The coronal, sagittal, and axial views are all part of the T1-CE MRI modality. It includes 1426 brain MRI images with glioma (corresponding to 89 patients), 708 meningioma photos (related to 82 patients), and the remaining 930 pituitary tumor images (belonging to 62 patients). Each image is 512x512 pixels in size and is accessible as.mat files. The input layer for GoogLeNet's original RGB colour image design had a size of 224x224x3.

F. Classifier Settings

1) Anisotropic filtering: The primary goal of image filtering is to eliminate noise from digital photographs. The noises severely impair the image's quality. The noise in the image can be removed in a variety of methods. In a noisy environment, the majority of image processing algorithms struggle to function. Fig. 2. Indicate the pre-processing tool is the image filter. Anisotropic Filter, one type of filter, is utilized in the propsoed approach for denoising. In order to explain the image diffusion process, the generic anisotropic diffusion equation is introduced as follows*:*

$$\frac{dx}{dy\cdot} = \mathrm{div}(\ c(m,n,t)\nabla c \cdot \nabla x + c(m,n,t)\nabla x \tag{7}$$

where, c (m, n, t) is the diffusion coefficient and ∇ is the image gradient.

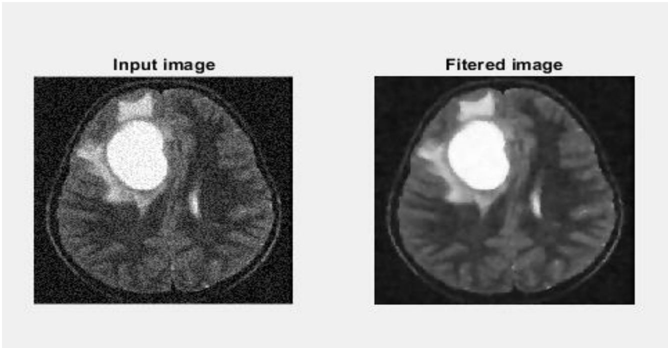
The signal pixels exhibit weak diffusion action, noise pixels exhibit high diffusion action. As a result, noise can be reduced while maintaining the signal. The fixed step size for each iteration or the entire iterative process of the image can be adopted by a variety of diffusion models. Here, a more effective iteration step is suggested in the equation, where 1/4 is employed to guarantee the equation's convergence.

$$dt = \frac{1}{4}c \tag{8}$$

Iterative processes are used to produce the final output phase image. Iteration error (IE), whose formula is used to manage the iterative number during the iteration process.

$$1E = \frac{\|I^n - 1^{n-1}\|}{\|1^{n-1}\|} \leq T_i e \tag{9}$$

The iterative procedure is terminated by IE ⩽ Tolerance (Tie).



(a) (b)

Fig. 2. Input and output of anisotropic filter.

2) Support vector machine filtration: In order to avoid over-fitting and local minima and improve generalisation capabilities, SVM relies on a different induction principle known as structural risk minimization. Algorithms for SVM use a set of mathematical functions referred to as the kernel. SVM has proven to have greater generalisation abilities in spare samples and high dimensional space. The goal is to locate the best separating hyperplane that can accurately categorise all samples. Image segmentation is the process of dividing an image into different sections. Data is inputted into the kernel, which then transforms it into the desired form [25]. SVM employ a variety of kernel functions, including sigmoid, radial basis function (RBF), polynomial, linear, and nonlinear. For sequence data, graphs, text, pictures, and vectors, kernel functions may be introduced. However, RBF is the most popular type of kernel function because it has a localised and finite response along the entire x-axis, doesn't increase computational complexity, effectively overcomes the problem of dimensionality, and returns the inner product between two points in an appropriate feature space. The maximum-margin hyperplane can be fitted using KSVMs in a changed feature space. In Fig. 3, the classifier may be a hyperplane in the higher-dimensional feature space, but nonlinear in the original input space if the transformation is nonlinear and the transformed space is higher dimensional.

Formula for defining a hyperplane is

$$P(x)= \propto O+\propto T\ z \qquad (10)$$

where, $\propto$ is the Weight vector, $\propto o$ is the Bias and z is the training instances that are closest to the hyperplane. Best Possible Plane Legation is

$$|\propto 0+\propto T\ z| = 1 \qquad (11)$$

The distinction between a point z and a hyperplane is revealed in the result.

$$(\propto, \propto o)\text{: } D = \frac{|\alpha_0+\alpha^1 z|}{\|\alpha\|} \qquad (12)$$

The canonical hyperplane's numerator is one, and the difference between it and the support vectors is,

$$D = \frac{|\propto_0+\propto^T z|}{\|\propto\|} = \frac{1}{a} \qquad (13)$$

For the canonical hyperplane, the numerator is equal to 1, and the difference from the support vectors is,

$$M = \frac{2}{a} \qquad (14)$$

In the end, the maximising problem for M and the minimising problem for a function are the same. R ($\propto$) is constrained in numerous ways.

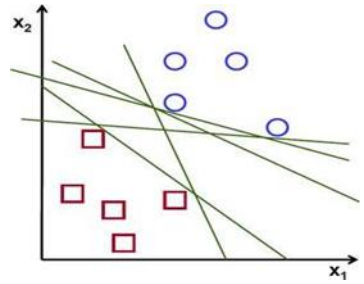


Fig. 3. Find a separating straight line for a set of 2D points that may be linearly divided into two classes.

3) Deep convolutional neutral network features: On a variety of difficult visual analysis tasks, deep convolutional neural networks have been consistently outperforming other methods. Recently, deep convolutional neural networks have been used to classify images from enormous image datasets. In order to enable the description of latent concepts for pattern recognition, a deep CNN is able to automatically learn fundamental filters and combine them in a hierarchical manner. However, overfitting and lengthy processing times are issues with many deep CNNs. In order to learn the characteristics of brain MRI pictures with tumors, the suggested algorithm makes use of updated and improved GoogLeNet. In the remainder of the paper, the features retrieved using a modified version of GoogLeNet will be referred to as deep CNN features. GoogLeNet is referred to as a deep network, having a total of 22 learnable layers [26]. It has a fully connected layer, nine inception modules, two pooling layers, two convolutional layers, and two pooling layers. Once more, an inception module has a pooling layer in addition to six convolution layers. The architecture of the module includes filters in the sizes 1x1, 3x3, and 5x5. It is anticipated that filters with various kernel sizes will detect various data patterns. At the conclusion of each module, the feature maps corresponding to various filters are concatenated. Additionally, smaller kernel convolutions are carried out before bigger kernel convolutions. They are designed to reduce computations' dimension. The training set was used to train the modified GoogLeNet (after pre-processing). Heuristic adjustments were made to the network's hyperparameters to speed up the convergence of the loss function during training.

Deep convolutional neutral network with features with support vectuor machine classifier: The modified GoogLeNet's pooling layer, which was implemented after the previous inception module, was used to extract features. After that, the traits were categorised using SVM. We used a multi-class SVM model with error-correcting output code (ECOC). A onevs-all strategy was used for multi-class categorization. There were three binary SVM learners with linear kernels.

Principles of Linear SVMs:

Given an N-size, p-dimensional training dataset of the following kind

$$\{(x_n, y_n)|X_n \varepsilon R^p, y_n \varepsilon(-1+1)\}, n = 1, \dots, N \quad (15)$$

where, either y_n is -1 or 1, which corresponds to class 1 or class 2. A p-dimensional vector represents each x_n. We want the support vector machine that separates class 1 from class 2 along the maximum-margin hyperplane.

$$wx^- = b0 \quad (16)$$

where, W is the hyperplane's normal vector and represents the dot product. The W and b should be chosen to maximise the margin between the two parallel hyperplanes while maintaining data separation. Thus, we use the following equations to define the two parallel hyperplanes:

$$wx^- = b1 \quad (17)$$

Binary SVMs pick up on the decision function f(.; w, b): X R defined by f (x; w, b) = w, (x) > +b. Let Y now be a collection of t > 2 classes, which stands for the classes of tumor types. Now, we're going to take a look at t output functions, one for each class, that express the degree of certainty for each prediction. Equation defines the output function for a stylish ∈Y.

$$F(x, \omega, b) = \langle w, \varphi(x)\rangle > +b \quad (18)$$

To boost the forecast's level of confidence, the predicted class yb for a given point x is determined, with the formula yb = argmaxyY fy (x; w, b). Finding w and b parameters that, at the very least, substantially result in accurate predictions and satisfy equation is what training is all about. w, b; fyi(xi) > fu (xi; w, b).

IV. Results and Discussion

The performance of the proposed approach is validated using performance matrices like Accuracy, Precision, F-measure and Loss. The MATLAB application from MathWorks is used to carry out the experimental process. Brain tumors are recognised by a GoogLeNet deep learning algorithm. The Convolutional Neural Network and Sector Vector Machine are coupled to choose and classify the features (CNN-SVM). Anisotropic filter is utilized as a pre-processing tool, while morphological analysis is used as an optimisation tool. The values of the underlying variables should be generated using the continuity equation in order to evaluate the efficacy of the suggested approach.

A. Metrics for Performance

The measurements for the suggested model are provided in the section, some of which have been examined and verified. The following mathematical diagram illustrates the study of performance measures [6]:

1) Accuracy: Many correct patterns to the total number of patterns is how accuracy to precision ratio is calculated.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \quad (19)$$

2) Precision: Precision is the ratio of positively anticipated values to all positively predicted values.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (20)$$

3) Recall: The true positives and false negatives numbers are obtained using the recall measure. The equation below shows that the recall and sensitivity are both known quantities.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (21)$$

4) F-score: The precision and recall values that are combined to get the F-score are used to calculate the score. The observation can be used to calculate the recall and precision weighted average.

$$\text{F-score} = 2\,\frac{\text{precision} \times \text{recall}}{\text{precision}+\text{recall}} \quad (22)$$

5) Loss: One maximum performance metric to evaluate the effectiveness of the SVM classifier. Moreover, it is evaluated using the error function.

B. Performance Analysis

The suggested model outperforms previous models, as shown by the statistical statistics provided above. The proposed approach is illustrated and flowchart in Fig. 4 in the approach recommended in the suggested technique.

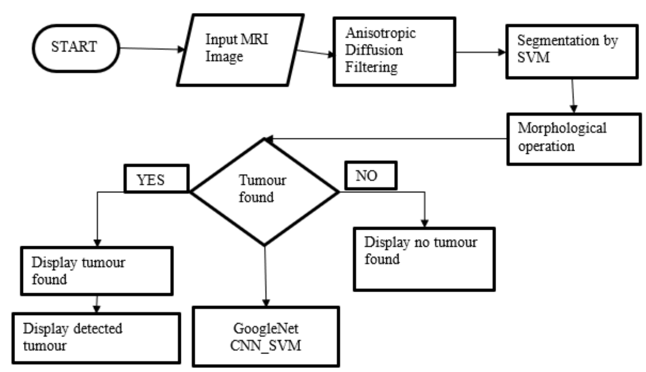


Fig. 4. The proposed methodology's flowchart process.

TABLE I. Comparison of the Proposed and Existing Methods' Performance

Predictive Methods	Performance of Classifier				
	Accuracy	Precision	Recall	F-Measure	Loss
DNN	0.8641	0.8365	0.8254	0.86	1.6522
SVM	0.7225	0.7212	0.7356	0.73	1.2566
ANN	0.8316	0.7963	0.7792	0.83	0.9325
Hybrid CNN-LSTM	0.9785	0.9538	0.9781	0.96	0.7840
Proposed Method	0.9864	0.9317	0.9860	0.97	0.8630

In Table I, accuracy is represented by 0.9864, precision by 0.9317, recall by 0.9860, F-measure by 0.97, and loss using the proposed technique is represented by 0.8630. The accuracy rating for the Hybrid CNN-LSTM is 0.9785, the precision rating is 0.9538, the recall rate is 0.9781, the F-Measure is 0.96, and the loss rate is 0.7840. The accuracy rating for the

ANN method is 0.8316, the precision rating is 0.7963, the recall rate is 0.7792, the F-measure is 0.83, and the loss rate is 0.9325. Precision, recall, accuracy, and loss value for the SVM technique are 0.7225, 0.7212, 0.7356, and 1.2566, respectively, for the overall F-measure. Additionally, using the DNN technique, the accuracy is 0.8641, precision is 0.8365, recall is 0.8254, F-Measure is 0.86, and loss is 1.6522.

In Fig. 5, the accuracy of the CNN-SVM brain tumor detection is displayed. It takes about 32 seconds to complete the training process and displays the accuracy result with 58 epochs per iteration. Also, the accuracy is indicated by the blue graphical line. As a result, for a successful evaluation procedure, the performance of the proposal can be trained and validated. As a result, the performance is quite effective for the suggestion.

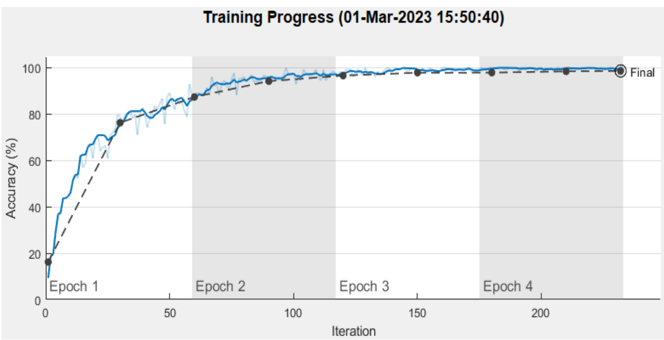


Fig. 5. The results that are accurate based on the graphical representation.

As seen in the graph below, the suggested attribute selection utilising the CNN-SVM model results in a loss with the least degree of detection error. When iteration is increased, the detection error of the suggested solution decreases. The suggested methodology is shown to improve accuracy and error function as a result. Fig. 6 Illustrates the loss function of the transfer learned model during training.

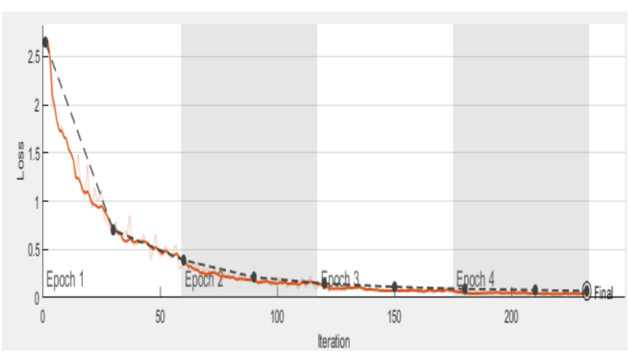
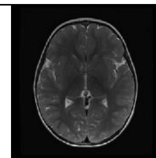
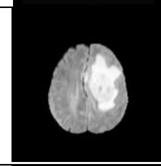
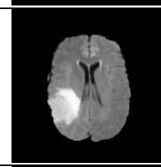
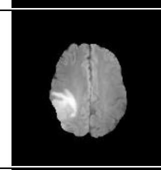
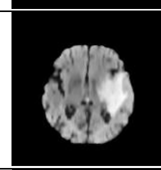
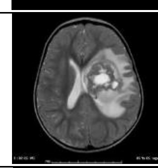
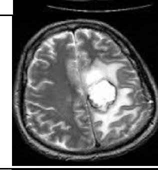
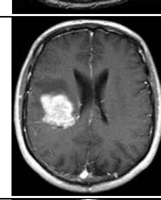


Fig. 6. The loss function of the transfer learned model during training.

The model's accuracy is demonstrated in Table II. By analysing the results and processing time. It may also be concluded that processing speed and results depend on the gradient of the pixels, the size of the image, and the quality of the image.

TABLE II. THE RESULTS OF THE TIME RESEARCH ON VARIOUS IMAGES OF BRAIN TUMORS SHOWING HOW TIME DEPENDS ON THE PREDICATED CRITERIA

No	MRI Brain Image.jpg	Preprocessing Time in seconds	Type of Image	Remarks	ACC %
i		16.268	_	Tumor not found	97
ii		19.989	Benign	Tumor found	99
iii		14.719	Benign	Tumor found	98
iv		29.401	Benign	Tumor found	99
v		11.451	Benign	Tumor found	96
vi		12.866	Malignant	Tumor found	95
vii		11.121	Malignant	Tumor found	97
viii		13.275	Malignant	Tumor found	99
ix		14.224	Malignant	Tumor found	96
x		16.263	_	Tumor not found	99

V. Conclusion

The proposed research combines Deep CNN characteristics and an SVM classifier powered by GoogLeNet's convolutional neural network (CNN) to segment brain tumors. The modified GoogLeNet's pooling layer, which was implemented after the previous inception module, was used to extract features. After that, the traits were categorised using SVM. Image processing has been successfully used to locate tumors in MRI brain scans, efficiently identifying the tumor's position by illuminating the area if it were there.

A database of 2D tumor image data is generated from the MRI scans acquired from different angles of a specific patient and the images are analyzed to pinpoint the precise 3D location of the tumor. The proposed method of classifying brain images using CNN and SVM has the potential to be a useful tool for computer assisted clinical diagnosis. The attributes increased performance when employed with tested classifier models. The most significant new finding of the study is a strategy for integrating them to distinguish between benign and malignant MRI brain as it produces a successful early tumor detection technique using computer-aided diagnosis. Early detection of brain tumors can benefit patients, healthcare providers, and the healthcare system as a whole. Patients can benefit from early detection by receiving timely treatment, which can improve their chances of survival and reduce the risk of complications. Healthcare providers can benefit by being able to provide more effective treatment and improve patient outcomes. Early detection can also reduce healthcare costs associated with treating advanced stage tumors. Additionally, early detection can enable researchers to better understand the disease and develop more effective treatments.

The future work can be advanced by regularly improving the model's accuracy by training it on larger and more comprehensive datasets. Several improvements are still feasible despite the successes presented in this research; there was a significant misclassification of samples from the dominant, and the phenomena of overfitting with smaller training data was noted. These problems should be addressed in the domain's future study, perhaps with data augmentation and additional fine-tuning of the transfer learnt model.

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