Brain Tumor Classification using Adaboost with SVM-based Classifier (ASVM) on MR Imaging

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Abstract

Among malignant disorders, the brain tumor is the most threatening. When contrasted to other diseases, the odds of dying from a brain tumor are higher. Early identification of brain tumor is crucial to reduce the risk of fatality. Brain tumor segmentation, which entails the extraction of tumor patches from data's, is top most difficult problems in the medical field. Due to the resemblance between cancerous and non - cancerous tissues and the wide variety of tumor appearances, this task is usually performed manually by medical experts, which is not always transparent. As a result, automating medical image segmentation remains a significant difficulty that has piqued the interest of a number of scholars in recent years. At this time, one of the biggest active study areas in the field of medical image processing is the detection and categorization of tumors. The goal of this research is to use an adaboosted SVM-based component classifier to construct a model for brain tumor detection and classification, i.e., to determine whether the tumor is cancerous or non-cancerous. A U-Net architecture is used initially for image segmentation, and then an adaboosted SVM classifier is used for classification. The purpose of using UNET is to increase parameter distribution accuracy and uniformity in the layers. Because of the difficulties in training SVM and the disproportion between diversity and accuracy over basic SVM classifiers, the Adaboost with SVM-based classifier (ASVM) is typically deemed to violate the Boosting principle. The Adaboost classifier in the study trains SVM as the basic classifier, which gradually decreases as the weight value of the training sample varies. On test data, the average classification accuracy is 98.2 percent, much outperforming SVM classifiers without Adaboost.

Keywords: Medical image processing; Segmentation; Brain tumor; SVM Classifier; Adaboost; Classification; UNET

1. Introduction

Our body's basic structural unit is the cell. There are around 100 trillion cells in the human body, and they generally divide in a controlled manner. Tumor cells are formed when cells divide in an unregulated or inappropriate way [1]. Intracranial neoplasm, commonly known as brain tumor, is a type of tumor in which aberrant cell proliferation occurs within the brain. Cancer is becoming a more serious medical condition as the world's population grows. The able to spot and classify brain cancer is a crucial feature for the healthcare industry [2]. Specifically, the Machine Learning method properly performed out all of the intricacies of an image, as well as re-analyzing the most necessary details. A total of 688,000 persons in the United States are impacted by brain cancer. It is possible for an initial brain tumor to be either malignant or benign. Therapies vary according to the type of tumor, its size, and its location. Countless people all over the world are benefiting from new medical techniques that are extending their lives and enhancing their standard of living. Tumors are classified as cancerous and non-cancerous. The cancerous growth spreads rapidly and extends to other parts of the brain. The benign tumor develops gradually and seldom spreads to other parts of the brain. In the United States, around 78,000 brain tumor patients are expected to be diagnosed in 2018. There are around 26,000 dangerous tumors and approximately 53000 benign tumors. Brain tumors can be cured using a variety of medications and treatments. The presence of a brain tumor is shown by an MRI scan. T he death rate in 2015 was estimated to be around 229000. Currently, providing the client with suitable and precise treatment is critical.

There are several other diagnostic procedures such as mammograms, CT scans, and X-rays, but scientists and researchers find that using this non-invasive instrument to analyze the entire body and discover any abnormalities, cysts, or brain tumors is quite beneficial [3]. An MRI scan can lead to headaches, vomiting, and discomfort or scorching at the site of injection, among other things. Medical imaging is a technique that would be used to capture images of the body for medical applications such as examination and diagnosis. The uncontrolled development of cells and tissues in the head is known as a brain tumor. Because of its accurate determination of soft and hard tissues, it is ideal for detecting brain tumors. Because it does not employ potentially hazardous ionizing radiation, it is preferred. A brain tumor can be characterized in a variety of ways. It is classed as follows based on the tumor's origin. The primary tumor is: The tumor cell originates in the brain. Metastatic brain tumor is the term for a secondary tumor. The tumor cell originates in other places of the body before making its way to the brain. The most prevalent sort of brain tumor is this one.

It is categorized as follows based on the malignancy. Noncancerous tumor cells that are typical in size and structure make up a benign tumor. They usually don't spread to other sections of the body. Tumor cells in a malignant tumor are cancerous cells with unusual size and development. They have a proclivity for invading surrounding healthy cells. Tumor cells are evaluated based on their composition. This grade measurement provides information regarding the tumor's pace of growth throughout therapy. The magnetic resonance imaging (MRI) image is often used to assess and diagnose brain malignancies. In order to diagnose a brain tumor, accurate classification and detection are required. The author [4] suggested a method for accurately detecting and classifying brain tumors. Gradient intensity-based picture smoothness, image restoration, skull removal, fragmentation, extraction of features, and categorization are all processes in the approach.

Tumor Stage	**Tumor Growth**	**Rate of growth**
1	Almost Normal	stagnant
2	Bit Normal	stagnant
3	Anomalous	Growth Alive
4	Highly Anomalous	Brisk Growth

Table 1: Brain Tumor Grades

A feature learning method that improves the effectiveness of a machine learning approach for pixel-level detection of brain tumor locations in an MRI brain image. To build a feature set, this method employs image filtering-based feature extraction techniques. The feature representation is then mapped to a response set with specified tags [5]. A support structure from a MRI brain scan is utilized to create feature space and the output set, which are then used to generate a machine learning model. We used the taught models, as well as automatic approaches, to locate tumor and non-tumor zones in additional frame of the MRI image. Pixel-level feature learning and label extraction also allow for tumor identification at the pixel level. Nevertheless, because the strategy is strongly reliant on the availability and selection of a reference frame, picture fragmentation and binarization approaches are recommended. The disadvantage of this strategy is that it does not identify whether there are any alternative response set creation strategies that can effectively map the subspace to the response set.

A benign tumor can transform cancerous over time, and a moderate tumor might become a superior tumor. As a result, knowing the exact stage of the tumor is critical for suitable therapy. This model was created using 3064 images from the dataset, which includes three different types of brain tumors. Glioma, Pituitary Tumor, and Meningioma are the three forms of tumors. MRI, Spectroscopy, Fusion, and other techniques are used to treat them. MRI is the ideal imaging technology since it successfully identifies the following conditions: cysts, tumors, bleeding, edoema, and infections. The segmentation of acquired images, where the borders of items such as aberrant regions or organs are recognized in the images, is top most difficult area in medical analysis. The output of the segmentation method can be used to determine the area, eccentricity, bounding box, and orientation of a segmented tumor region. For segmentation, the UNET model is employed. One of the most important jobs in automatic image analysis is image segmentation. It entails breaking an image into its constituent pieces and extracting the feature points that should be uniform in terms of certain properties such as intensity or texture.

Early illness prediction can be done accurately using Machine Learning (ML) techniques. The classification algorithm is a type of machine learning strategy that classifies raw data into a target class while recognizing and extracting features from dataset. The goal of this study is to figure out a patient can have tumors in brain or not. This research shows how to detect brain tumors using ensemble-based machine learning algorithms. When compared to a single classifier model, adopting ensemble based approaches produces more accurate results. Ensemble approaches are meta-algorithms that combine outcomes from a number of different base models into a single predictive model. Boosting is a technique used in this paper to create an ensemble model. The AdaBoost technique is combined with SVM in this research; in the domain of brain tumor identification, a precise and effective classifier model with low classification error is desired. For improving the performance of the classification procedure, the AdaBoost algorithm requires fewer tuning parameters.

The paper is organized as follows. Section 2 describes a short literature overview of SVMs and brain tumor segmentation algorithms. Section 3 provides an outline of associated SVM implementation, while Section 4 discusses brain tumor classification and evaluation. Finally, Section 5 brings the paper to a close by outlining some possible future directions.

2. Literature Survey

The detection of brain tumors is a critical component of image recognition in the medical field [6]. The outcomes of this testing demonstrate that, prior to performing segmentation of the brain tumor region, filtering the median and stripping skull should be performed in the pre-processing step because Pictures comprise noise and the skull often have an intensity that is equivalent to the brain tumor area. A variety of svm models are employed in order to achieve an accuracy rate. The mean efficacy of the approach was found to be significantly higher than that of traditional models. Image properties such as contrast, correlation, energy, and homogeneity are calculated based on the GLCM algorithm. The photos will then be categorized using a support vector machine (SVM), for example, the image either with or without tumor will be classed as such. It is possible that additional machine learning techniques will be used in the future, allowing for increased reliability even for low-intensity photos to be obtained.

In [7], the classification method begins with preprocessing, which involves shrinking the MR image and injecting salt distortion to the image. Additionally, geometric enrichment is performed to enhance the database size before the classification cycle begins. A second step involves shuffling the photos from each type of tumor to divide the dataset into three parts: training, validation and testing. Because bio-medical pictures are hard to evaluate, CNN and SVM were selected for their ability to classify objects based on the degree of extracting features performed on them. CNN does the extracting by the use of convolution layers, and as the degree of the layer grows, the degree of feature rises. In contrast, in SVM, characteristics are retrieved based on the sort of texture or structure present in the image, and classes with similar characteristics can be categorized more readily than classes with different features. As a result, CNN and SVM-based designs are chosen to train on the training dataset, and then the trained model is evaluated on the validation and testing datasets. It has been discovered that while Polynomial SVM performs marginally better than Linear SVM, CNN performs significantly better than Polynomial SVM. Because of its much enhanced quality, it is determined that CNN is the best alternative for the most accurate and trustworthy categorization, as demonstrated above.

According to the [8], the hybridized attribute selection methodology presented in the study has been adopted and implemented, which has resulted in increased efficiency. After selecting a collection of integrated local and global features from magnetic resonance imaging (MRI) of brain pictures, their dimensions were decreased using Principal Component Analysis. The Gray Level Covariance Matrix was calculated based on these characteristics. In order to train the model, a collection of 26 features, of which 13 are local and 13 are global, are computed from GLCM and used in the process. The classifier model was tested on a set of test picture samples before being used. The experimental results are extremely encouraging, as the procedure achieves the highest level of accuracy possible. Before merging the characteristics, it is possible to experiment with different extraction of features strategies. These composite characteristics can be combined with a variety of classifiers to see whether a better appropriate model is possible.

The magnetic resonance imaging (MRI) technology is among the most widely utilized ways for examining types of brain tumors. For the categorization of photographs, there are multiple strategies and methods that can be used. The primary objective of this model and classification techniques is to learn automatically from training data and, at the end of the process, to make an informed conclusion with high precision. On the basis of MR brain image features, the effectiveness of tumor classification techniques multifocal, and multicentre tumors was investigated [9]. As part of the classification process, the statistical parameters of each of the input photos were examined, and the data was then methodically split into several groups. Several machine learning techniques were used to assess the data, including KNN, RF, SVM, and LDA algorithms. When comparing to other techniques, the SVM approach was proved to be better because it had a 90 percent accuracy rate.

Cerebrum tumor is a malignant neoplasm caused by abnormal or uncontrolled cell division in the brain. Cancer treatment can be extremely difficult if tumors are not detected early. Therefore, prompt diagnosis and treatment are essential. The author [10], discuss the detection of tumor regions using a Morphological Operators-based segmentation technique. It consists of three stages: upgrading, division, and placement. Using a classification system that separates benign from malignant images, it is possible to extract the tumor region from the photos. When compared to clinical approaches, the automated segmentation technique takes less time to calculate the tumor area since it is more accurate. This methodology has been investigated, and the mathematical findings have been contrasted to those obtained by other methods now in use. In the case of brain tumor identification, the integration of methods such as Morphological Operators and support vector machines yields more precise results. This strategy could save time when there are a large number of photos.

The authors of [11] proposed utilizing SVM with otsu's thresholding method to classify MRI brain tumor images and segment them. This method is designed for image categorization using intensity and textual features, followed by PCA and SVM processing. The results of fuzzy c-means clustering, k-means, and KIFCM were then evaluated. Thresholding is done on the basis of intensity. It is the most essential image processing and computer vision technique. It transforms the grayscale image to a binary, which enables extracting essential information from the MRI image smoother.

3. Proposed Model

Although there are a number of automatic algorithms for MRI image segmentation and classification, they still need to design a well organized and quick approach. Early tumor diagnosis is aided by proper tumor segmentation. As a result of this research, the Adaboost with SVM-based component classifier (ASVM) classifier was created for brain tumor diagnosis. This program employs the principles of data collecting, data preprocessing, segmentation, classification, and accuracy estimations in order to detect brain tumor disease. As shown in Figure 1, the suggested system's architecture. The preprocessed data will be segmented using UNET, and then classified using ASVM. This will make it easier to tell the difference between cancerous and healthy cells. The parametric analysis of brain imaging reveals whether or not a tumor is present depends upon on the simulation results.

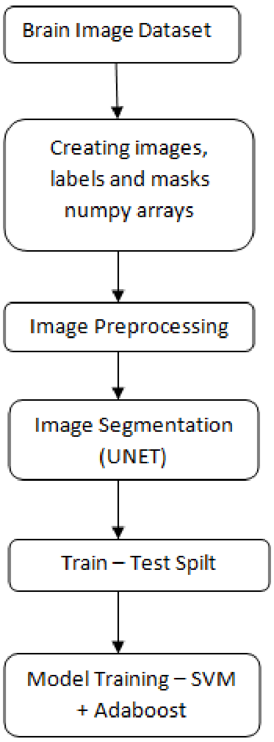

Figure 1: Block Diagram for proposed system

This brain tumor dataset have 3064 images divided into three groups. 1. Glioma 2.Pituitary 3.Meningioma. There are 1047 coronal pictures accessible in total. Coronal images are acquired from the back of the head. Axial pictures, or images taken from above the head, number 990. The dataset also includes 1027 sagittal images, which were taken from the side of the head. A label specifies the tumor kind in each image in this dataset. These 3064 images represent 233 different patients. The dataset contains 708 meningiomas, 1426 gliomas, and 930 pituitary tumors, which are split into three categories. Figure 2: Images from the dataset.

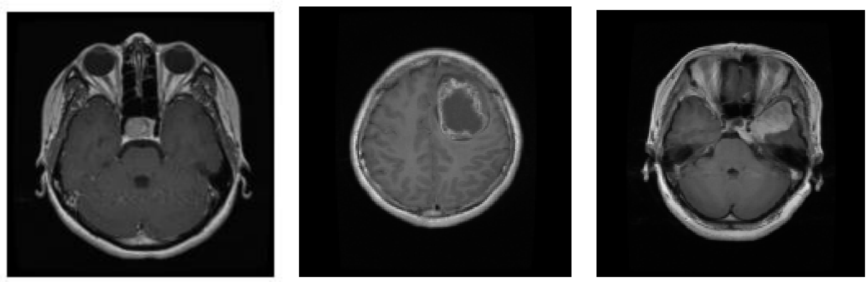

Fig.2. Sample images of: (a) Pituitary (b) Glioma (c) Meningioma

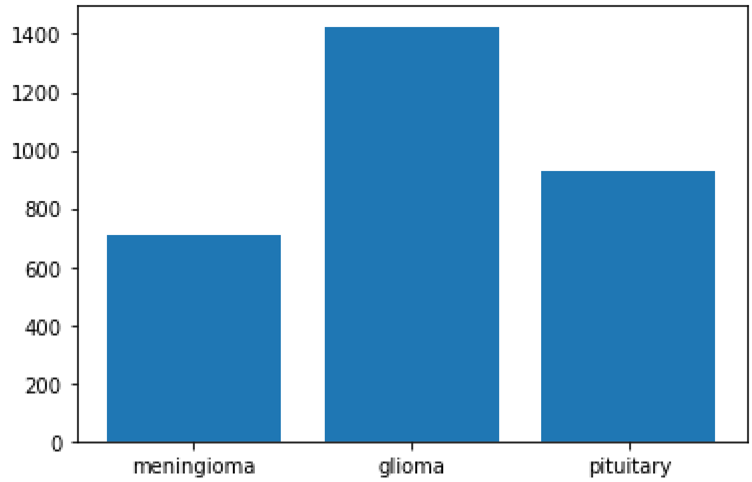

Figure 3: Number of image in each category

For real-world data, which is frequently noisy and unreliable, image pre-processing is critical. The goal of this phase is to increase the image's quality by converting it into a different image that is better suitable for machine analysis. The term "preprocessing" refers to operations on images at the most basic level of abstraction. To load the Mat formatted data and convert it to PNG format, we'll utilize hdf5storage. The image and mask must then be resized to a specific size. To numpy arrays, add images, labels, and masks. At this point, the image trimming procedure begins by locating brain areas that will be used in the following step and eliminating background items that will not be required. This approach is designed to limit the likelihood of issues such as tumor object detection inaccuracy during the segmentation step altering the outcomes of the features collected. Figure 4 shows a few of the cropped photos. Because most deep learning model designs require all input photos to be of the same proportions, image resizing is required.

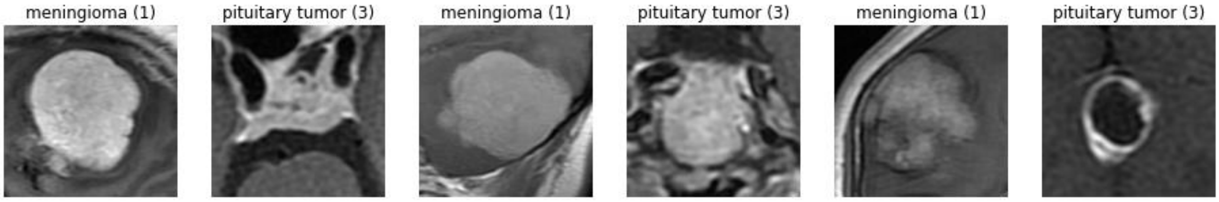

Figure 4: cropped images

UNet has developed with just minor alterations to the CNN architecture. It was created to deal with biomedical images in which the objective is to not only categories whether or not there is a disease, but also to locate the infection region. The intended outcome of many visual tasks, particularly in biological image analysis, must contain localization, i.e., each pixel should have a class label. Furthermore, in scientific jobs, thousands of training photographs are usually out of reach. As a result, we employed a sliding-window strategy to train a network to find the most likely label of each pixel using a small patch around each pixel as input. This network has the ability to localize, and the training data vastly outnumbers the number of training photographs in terms of patches. To begin with, it's slow because each patch necessitates a fresh network run, and there's enough reiteration owing to crossing patches. Second, there is a swap in localisation between precision and context usage. Bigger patches necessitate lot of max-pooling layers, limiting localisation accuracy; however, the network can only recognize a limited amount of context thanks to the small patches.

We improve and adopt a more elegant architecture in this study so that it can work with less training data and deliver more exact segmentation results. The primary idea is to replace pooling operators with sequential layers to supplement a standard contractual network. As a result, using these layers improves the output resolution. To localise, the upsampled output is combined with the contracting path's higher resolution features. Based on this knowledge, a subsequent convolution layer could produce a more exact output. In many cell segmentation tasks, separating touching objects of the same class is a problem. We propose utilizing a weighted loss function to do this, with the separating background labels between interacting cells given a high weight in the loss function. The segmentation of biomedical data is made easier with the help of this network.

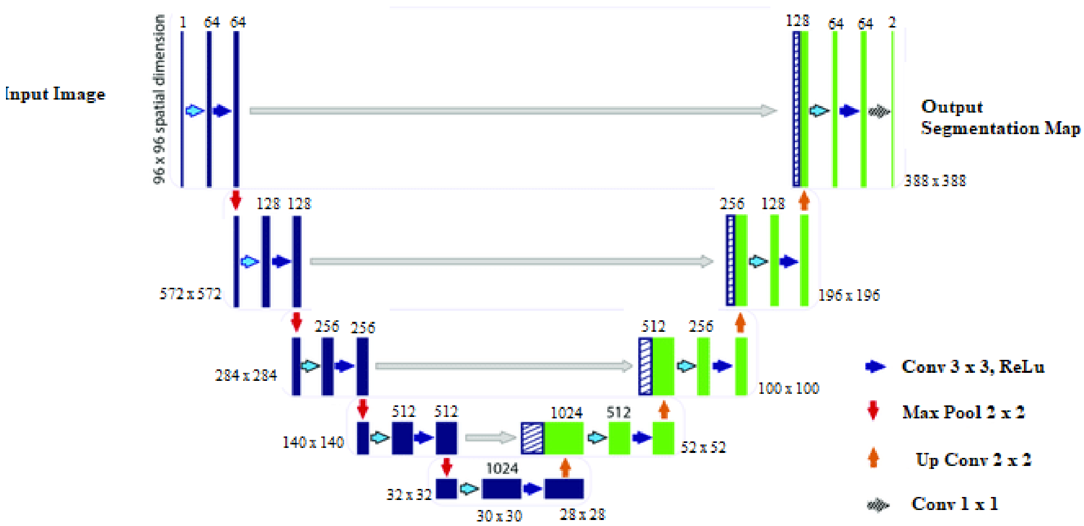

Figure 5: Architecture for the 2D U-Net

Adaboosted SVM (ASVM) Algorithm

Support vector machines (SVM) are supervised learning models that build a hyper plane or series of hyper planes in a large or immeasurable dimensional hole with the goal of separating data into two groups as efficiently as possible. It is built on top of the assessment plane, which establishes the resolution limits. In order to increase performance, the ensemble method is utilized for unstable classifiers. AdaBoost (Adaptive Boosting) is a machine learning meta-algorithm that combines prior approaches into a weighted sum that represents the boosted classifier's final outcome set of training samples. For each sample, it keeps track of weight. Weights are adaptively controlled for each iteration. Component classifiers with AdaBoost have a harder time with greater weights. It also makes an assessment using all of the constituent classifiers. It is susceptible to data that is noisy. It's less prone to over-tightening.

It's quick, easy to program, and versatile, with only one parameter to tune: t. its drawbacks include poor classifiers that are overly complicated, resulting in over-fitting. Apart from the experimental evidence, AdaBoost is particularly vulnerable to homogenous noise. The standard empirical risk deprecation strategy, which decides the decision function as.

$$L = \frac{1}{n}\sum_{i=1}^{N}|f(x_i) - y_i| \qquad (1)$$

Where N is the samples size and f is the classification decision function, sequentially. The decision function in the linearly separable problem is:

$$f_{v,b} = Sign(v.x + b) \qquad (2)$$

For the linearly non-separable cases needs to be alter to grant the scrampled data points. The decision function Eq.(2) can be rewritten as

$$f(x) = sign(\sum_{i=1}^{N} y_i \tau_i^*(x) + b^*) \qquad (3)$$

We may expand the SVM in two different ways for multi-class classification. One way is the "one-against-all" method, in which the no. of SVMs is equal to the no. of classes. The decision function becomes

$$f(x) = sign(Max_{j\epsilon 1,2,\ldots c}\left(\left(w^j\right)^T.\varphi(x_i) + b_j\right)) \qquad (4)$$

Algorithm: The Adaboosted SVM Algorithm

No. of patterns is n, training set; x training samples, [x1,x2, . . . xn];

y: labels, [y1, y2, … yn];

k_{max}: Max no. of classifier;

W_k : weight distribution at iteration k, [$W_k(1)$, $W_k(2)$… $W_k(n)$]

Step 1: $w_1(i)$= 1/n, i= 1,……, n initialize weights,

Step 2: K=1; $\gamma = \gamma_{ini}$ set these values

K < k_{max} do

K=k+1, increment

Step 3: Temporary training set, x^{train}, train component classifier C_k using. sampled from x according to W_k;

Total diversity calculate if classifier C_k is added:

$$DI = \frac{1}{kN}\sum_{i=1}^{k}\sum_{i=1}^{N} d_{xi}$$

$$\mathrm{dxi} = \begin{cases} 0 \text{ if } g_t(\mathrm{xi}) = f(\mathrm{xi}) \\ 1 \text{ if } g_t(\mathrm{xi}) \neq f(\mathrm{xi}) \end{cases}$$

The detection label of Classifier the k^{th} in the x_i and $f(x_i)$ is the combining detection of t^{th} component classifier in the sample x_i

Step 4: If(Ek>0.5) OR (DI<DIV), $\gamma = \gamma_{step}$

Classifier weight calculate. $\alpha_{k=0.5log\left(\frac{\varepsilon_i}{1-\varepsilon_i}\right)}$

Where $\varepsilon_k = \sum_{i=1}^{n} \beta_i$

Step 5: Update weight, $W_{k+1}(i) = W_k k(i) x \begin{cases} e^{-p(y_i|x_i)} if\ p(y_i|x_i) \geq p(y_j|x_i)\ for\ \forall i,j \\ e^{p(y_i|x_i)},\ Otherwise \end{cases}$

Normalize weights, $W_{k+1}(i) = \frac{W_{k+1}(i)}{\sum \forall_j W_{k+1}(j)}$

Ensemble of classifier and weights α_k

end.

4. Results and discussion

This brain tumor collection contains 3064 T1 weighted pictures of three types of tumors. The database is in Mat format. The images are then converted to PNG image format before preprocessing. UNET is used to segment the preprocessed image, and KNN is used to train the model. We bifurcate the data into two categories: train and test, with training accounting for 80% of the data and testing accounting for 20%. With SVM, we were able to obtain a 91.9% accuracy rate. ASVM has developed as a new methodology for detecting brain tumor disease that uses classify the disease with a high accuracy rate of 95.2%. In the adaboosted svm-based component classifier, BKNN is implemented by using KNN as the base estimator. The proposed solution is implemented using Python, an open source programming language, with Jupyter NoteBook serving as a medium for developing these codes. The produced scenarios are appropriate and intelligent for detecting disease utilizing real-time datasets and training norms. One of the brain tumor image (Meningioma) is displayed in figure 6.

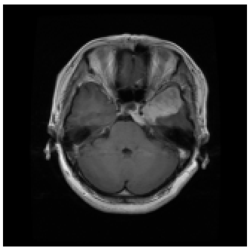

Figure 6: Input image

The image is handled at this phase to improve image quality and standardize the variables in each training image. As a result, the image displays findings that are not significantly different. The mat-formatted input files are first converted to png-formatted data. Crop an image to its bounding box by forcing a squared image as the result after preparing the original image, as seen in figure 7. Cropping an image is required to centre the brain image and remove superfluous sections of the image. Additionally, within the overall image, various brain images may be positioned in different locations. By cropping the image and adding pads, we can ensure that almost all of the photos are in the same place inside the overall image.

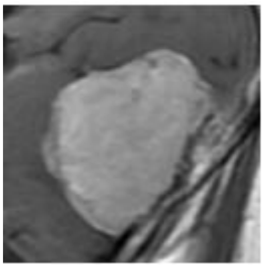

Figure 7: Cropped input image

The Figure 8 shows the segmented input image. The UNET architecture is deployed for image segmentation and Tumor plot is shown below.

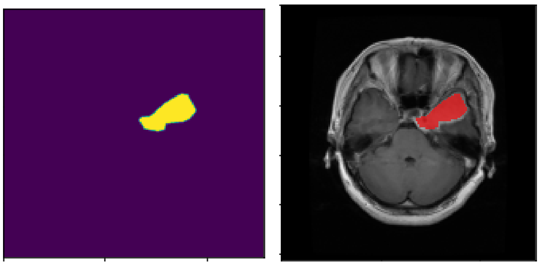

Figure 8: Segmentation of the input image

These segmented photos are separated into a train-test split function, with 80% of the images for train a model and the remaining for test the model. The model will then be trained using ASVM, and its performance will be evaluated. The following figure, Fig-9 illustrates the perception of Confusion Matrix of the ASVM Model. We measure the effectiveness of our model with the help of confusion matrix

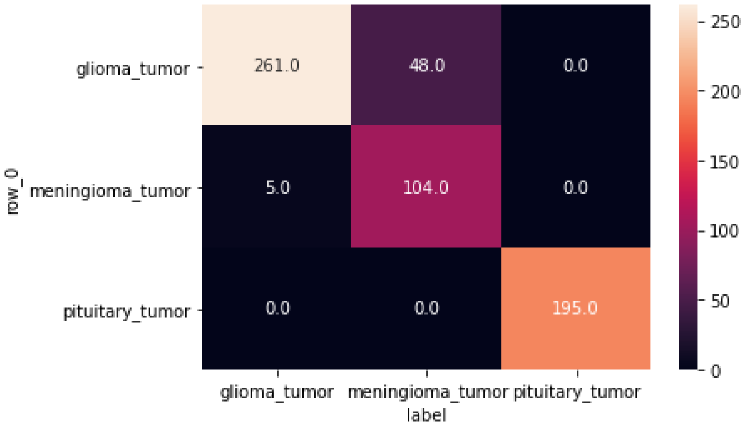

Figure 9: Confusion Matrix

The classification report for our proposed model is shown in Figure 10. In machine learning, a classification summary is a required to indicate the execution review. It's used to give an idea of your trained classification model's precision, recall, F1 Score, and support. The classification accuracy is equal to the total no. of correct predictions divided by the total no. of predictions created for the dataset. Precision is the no. of positive class forecasts that truly belong to the positive class. Recall is the no. of positive class predicted from all positive cases in the dataset. F-Measure calculates a single score that takes into account both precision and recall problems.

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                  precision    recall  f1-score   support

    glioma_tumor       0.95      0.95      0.89       132
meningioma_tumor       0.90      0.73      0.80        84
 pituitary_tumor       1.00      1.00      1.00        91

        accuracy                           0.90       307
       macro avg       0.95      0.89      0.90       307
    weighted avg       0.95      0.90      0.90       307
```

	Glioma Tumor	Meningioma Tumor	Pituitary Tumor
Sensitivity	0.954265	0.897059	1.000000
Specificity	0.955975	0.903766	1.000000
Fall out	0.044025	0.096234	0.000000
False negative rate	0.044025	0.096849	0.000000

Figure 11: Sensitivity, Specificity, Fallout & False negative rate of ASVM

The table above shows the model's sensitivity, specificity, fallout, and false negative rate. The true positive value of a test refers to the percentage of data that is genuinely positive and results in a positive result when the test is used. The genuine negative rate commonly referred to as the specificity of a test, is the percentage of data that is actually negative and yields a negative result. Figure 12 depicts the impression of the suggested ASVM accuracy ratio, which has been cross-validated with classic classification techniques such as SVM. The proof that emerges visually illustrates the effectiveness of the suggested strategy.

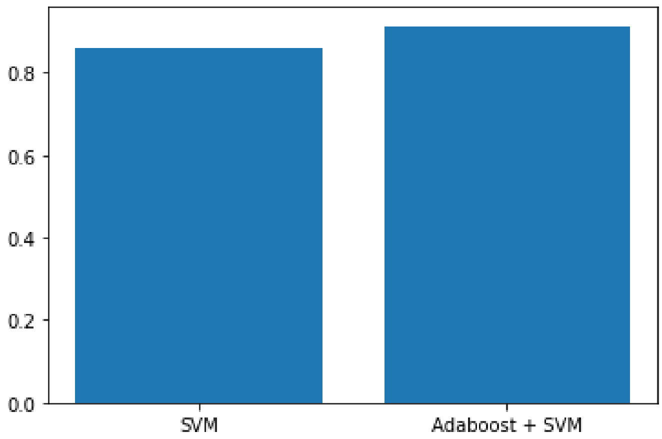

Figure 12: Accuracy Comparison Graph between SVM and ASVM

5. Conclusion

Despite the fact that MRI imaging is one of the most modern techniques for detecting brain malignancies, specialists who rely entirely on MRI data are unable to keep up with diagnosis. As a result, computer-assisted diagnosis is required for accurate brain tumor classification. Medical image segmentation software has previously proven its worth in research applications, and it is currently being employed for computer-assisted diagnosis and radiation planning. The U-net architecture, one of the most widely used and best-performing architectures, was proposed in this work for medical image segmentation. We developed a novel approach for detecting brain cancers using an adaboosted SVM classifier (ASVM). ASVM is applied in the Boosting classifier by utilizing SVM as the base estimator. The overall classification accuracy was up to 95.2%, which is higher than existing methods. Supervised approaches, such as KNN ensemble with Bagging, may be utilized in the future to better classification accuracy.

References

[1] Sathies Kumar, Rashmi, Sreevidhya Ramadoss, "Brain Tumor Detection Using SVM Classifier," 2017 IEEE 3rd International Conference on Sensing, Signal Processing and Security (ICSSS).

[2] S. Gayathri, D. C. J. W. Wise, V. Janani, M. Eleaswari and S. Hema, "Analyzing, Detecting and Automatic Classification of Different Stages of Brain Tumor Using Region Segmentation and Support Vector Machine," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020, pp. 404-408, doi: 10.1109/ICESC48915.2020.9156057.

[3] S. Razzaq, N. Mubeen, U. Kiran, M. A. Asghar and F. Fawad, "Brain Tumor Detection From MRI Images Using Bag Of Features And Deep Neural Network," 2020 International Symposium on Recent Advances in Electrical Engineering & Computer Sciences (RAEE & CS), 2020, pp. 1-6, doi: 10.1109/RAEECS50817.2020.9265768.

[4] M. A. Kabir, "Early Stage Brain Tumor Detection on MRI Image Using a Hybrid Technique," 2020 IEEE Region 10 Symposium (TENSYMP), 2020, pp. 1828-1831, doi: 10.1109/TENSYMP50017.2020.9230635.

[5] R. Joshi and S. Suthaharan, "Pixel-Level Feature Space Modeling and Brain Tumor Detection Using Machine Learning," 2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA), 2020, pp. 821-826, doi: 10.1109/ICMLA51294.2020.00134.

[6] A. Hussain and A. Khunteta, "Semantic Segmentation of Brain Tumor from MRI Images and SVM Classification using GLCM Features," 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA), 2020, pp. 38-43, doi: 10.1109/ICIRCA48905.2020.9183385.

[7] S. K. Baranwal, K. Jaiswal, K. Vaibhav, A. Kumar and R. Srikantaswamy, "Performance analysis of Brain Tumour Image Classification using CNN and SVM," 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA), 2020, pp. 537-542, doi: 10.1109/ICIRCA48905.2020.9183023.

[8] S. Kumar C.K. and H. D. Phaneendra, "Categorization of Brain Tumors using SVM with Hybridized Local-Global Features," 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), 2020, pp. 311-314, doi: 10.1109/ICCMC48092.2020.ICCMC-00058.

[9] G. Çınarer and B. G. Emiroğlu, "Classificatin of Brain Tumors by Machine Learning Algorithms," 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), 2019, pp. 1-4, doi: 10.1109/ISMSIT.2019.8932878.

[10] R. M. Mapari and H. G. Virani, "Automated Technique for Segmentation of Brain Tumor in MR Images," 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), 2019, pp. 867-870, doi: 10.1109/ICOEI.2019.8862531.

[11] Rani, R., Kamboj, A., "Brain Tumor Classification for MR Imaging Using Support Vector Machine". In Progress in Advanced Computing and Intelligent Engineering (pp.165-176). Springer, Singapore (2019).