International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
DOI: https://doi.org/10.17762/ijritcc.v11i10.8427
***Article Received:** 22 July 2023 **Revised:** 10 September 2023 **Accepted:** 26 September 2023*

Brain Tumor Detection and Multi Classification Using GNB-Based Machine Learning Approach

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Abstract— In an abnormal tissue called a brain tumor, the cells of the tumor reproduce quickly. if no control over tumor cell growth. The difficulties involved in identifying and treating brain tumors Machine learning is the most technologically sophisticated tool for classification and detection, implementing reliable state-of-the-art A.I. as well as neural network classification techniques, the use of this technology in early diagnosis detection of brain tumors can be accomplished successfully. it is well known that the segmentation method is capable of helping simply destroy the brain's abnormal tumor regions In order to segment and categorize brain tumors, this study suggests a multimodal approach involving machine learning and medical assistance. Noise can be seen in MRI images. To make the method for eliminating noise from images easier, a geometric mean is used later. The algorithms used to segment an image into smaller pieces are fuzzy c-means algorithms. Detection of a specific area of interest is made simpler by segmentation. The dimension reduction procedure is carried out using the GLCM. Photographic features are extracted using the GLCM algorithm. Then, using a variety of ML techniques, like as CNN, ANN, SVM, Gaussian NB, and Adaptive Boosting, the photos are categorized. The Gaussian NB method performs more effectively with regard to the identification and classification of brain tumors. The plasterwork work achieved 98.80 percent accuracy using GNB, RBF SVM.

Keywords- Machine Learning, GLCM, Gaussian Naive Bayes, Adaptive boosting, MRI.

I. INTRODUCTION

Today, using information technology as well as ML in medical science is becoming more and more crucial. Making a machine that can understand on its own, without help from human bodies, and train itself to effectively manage potential cases by itself is the goal of artificial intelligence (AI). The implementation of this scientific knowledge is extremely relevant to the creation of brain tumor interventions because tumor cells exhibit wildly uncertain behavioral patterns that is too complex for conventional medicine to handle.

A brain tumor may develop as a result of inappropriate and extreme brain cell growth. The majority of cancer-related deaths in people under the age of 19 are caused by brain tumors, which account for 24% of all cancer-related deaths. There are about 120 distinct types of brain tumors. Due to this, specifically.it is getting harder to find medical care that is effective for a specific type of tumor. For classification objects, there are two different forms of tumors: benign as well as malignant. Brain tumors that are benign are less dangerous than those that are malignant. A tumor is considered "benign" if it does not spread to other body organs through metastasis when analysing the various types of cancer. Fewer people will die from this type of cancer. The most common treatment option for benign tumors, which are typically curable, is excision surgery. Cancerous tumors are notoriously challenging to remove and carry a risk of metastasizing to other areas of the human [1, 2].

However, if a person has a brain tumor, whether malignant or benign, they are in danger and may even die. Benign brain tumors may continue to grow outside of the tissues that surround them, and besides, as they expand, they can become more dangerous, they put added burden on nearby cells of the brain that are crucial for the healthy function of the brain, which can result in loss of the brain Brain tumors can develop from the brain tissue itself or from cancer cells that have metastasized to the brain from a different area of the body. This procedure, known as "metastasis," occurs when tumor cells from one organ move from one region to another and enter the tissue of the new area. [3,4]

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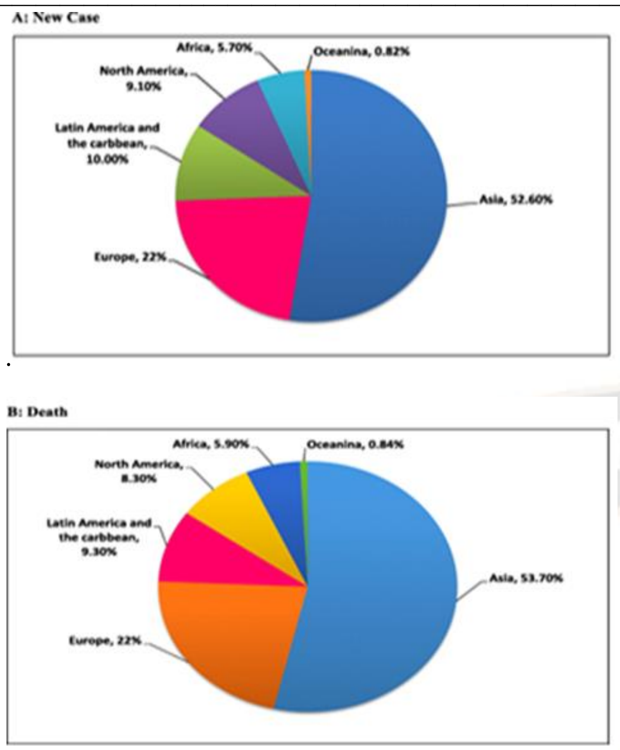

Fig.1: Word Brain tumor cases and death rate

This organization's primary objective is to research, identify and classify a wide range of brain disorders. This can be done using a standard MRI scan to produce a 3D representation of the brain. Radiation therapy is frequently utilized for treating cancer, and This treatment is frequently utilized by MRI segmentation. As an outcome, we are able to determine whether a tumor is present in a segment that an MRI detected. These procedures don't involve ionizing radiation.; rather, they serve the purpose of diagnosis, and disease stages are categorized, and monitoring is then performed. Hospitals are the place where these treatments are most frequently used. When a brain tumor is in a more advanced phase, MRI, Among the most beneficial techniques currently available, is utilized to diagnose it [5].

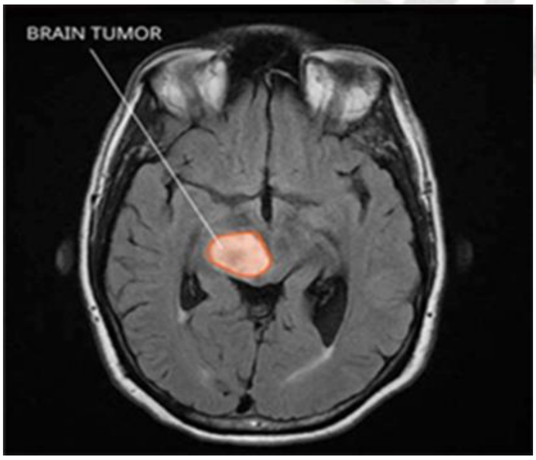

Fig. 2: Brain tumor MRI image

Segmentation is an important procedure to perform when scanning medical images for potentially dangerous areas. Automated recognition for the initial identification of cerebral tumors by MRI has a great deal of potential to be utilized and precision. Figure 1 shows an MRI of a brain tumor.

This article presents an evolutionary method for identifying as well as classifying brain tumors that uses machine learning and image processing. To categorise and identify brain cancer, this framework follows image pre-processing, image enhancement, segmentation, and machine learning algorithms.

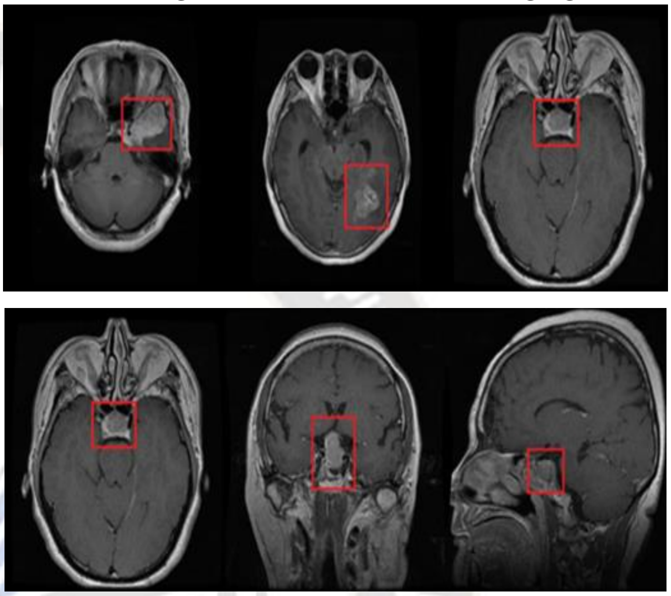

Fig 3: MRI images showing various tumors various kinds in a different plane

II. RELATED WORK

In a study by Bada and Barjaktarovic [6] from 2020, various tumors were categorised using a CNN model. An I source layer, 2 blocks "A," 2 blocks "B," a block of classification, as well as an outcomes layer made up the twenty-two layers of the system architecture utilised in the study. The k-fold cross-validation approach was used to assess the efficiency of a network. In this analysis, the better result for the tenfold cross-validation technique was 96.56%. Using 3064 T1-weighted contrast-improve MRI scans from Tianjin University Of Medical Sciences in China were utilized for this study's image database.

Gunasekara et al. [7] suggested found that CNN performed better than ML models in their comparison of various ML and CNN models in order to detect this condition. In order to identify the tumor regions of interest, a three-stage DL framework with classifiers was introduced in deep CNNs at the initial and second levels, respectively. The focused tumor boundaries are contoured using the ChanVese segmentation algorithm in preparation for segmentation in the following step. The typical dice result using this approach is 92 percent.

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Rezayi et al. [8] used DL networks like VGG-16 as well as ResNet-50 to find acute lymphoblastic leukemia. Ten convolutional layers in a CNN and 6 widely used ML algorithms were also provided by the authors to further divide leukemia into 2 categories.

Masud et al [9] .'s classification framework allowed them to distinguish between five separate lung as well as colon tissues, 2 of which were benign & 3 of which were malignant. The results show that this approach can predict the presence of cancer in tissues with accurate results of 96.33%.

Reshma et al. [10] carried out a number of works to learn more about how textural, morphological, as well as graph characteristics influence the categorization performance rate. CNN has been combined with a weighted feature selection technique and an enhanced genetic algorithm to identify breast cancer.

Khan et al. [11] The input was categorized into four different subgroups glioma, meningioma, pituitary, as well as non-tumor. They did this using a CNN-based hierarchical DL-based brain tumor classifier. In comparison to other methods currently being used to identify and segment brain tumors, this model's effectiveness of 92.13% is higher.

Mohanaiah et al. [12] It was suggested using an image recognition technique that extracts textural data from images. To retrieve textural characteristics, the GLCM approach was used. Without including texture analysis in the picture-sorting procedure, image analysis will be lacking.) To retrieve textural characteristics from grayscale images, use the GLCM algorithm. By utilising these criteria to the software used in medicine, diseases can be classified as either normal or abnormal. (This statistical method enables feature extraction.) The author evaluated the characteristics of image movements using this matrix methodology. An MRI image was utilized to assess characteristics like angular second scene (energy), correlation, and entropy.

Vaishnavee and Amshakala [13] The brain image segments were created using the SOM clustering offered. Histogram equalization is employed to obtain the characteristics prior to segmenting the images. PCA was used for feature selection as well as to improve classification performance. Additionally, proximal SVM classification methods were created; these were highly effective than SVM classification. His results demonstrate SVM classifiers are effective for extracting features from digital images.

Hemlatha et al. [14] found that by using the MRI approach, it was feasible to automatically determine a tumour's size and location in the brain. They have demonstrated how to do this by utilising digital image processing.

Megha et al. [15] show how and where to significantly enhance scene feature discrimination and suggested using quantitative methods to replace image data analysis visually, for an automated feature that indicates the type on the identification of every pixel in the image. They also demonstrated how to enhance the visual distinction between scene components. The processing of digital images has also been assumed for data extraction.

Rohini Paul et al. [16] recommended utilising K-means clustering technique in their research from 2014 to divide data acquired from brain MRI scans. When segmenting brain MRI for the object of tumor diagnosis, morphological filtering is absolutely essential to prevent the emergence of clustered regions .

III. METHDOLOGY

A. *Convolutional Neural Network*

A specific type of deep neural network is CNNs which filter their inputs for pertinent information utilising convolutional layers. In order to evaluate the outcomes of neurons that are linked to the particular local area in the input, CNN's convolutional layers apply convolutional filters to the input data. It makes it easier to extract temporal and spatial characteristics from images. Weight-sharing is a method used by CNN's convolutional layers to decrease the overall amount of parameters [17,18].

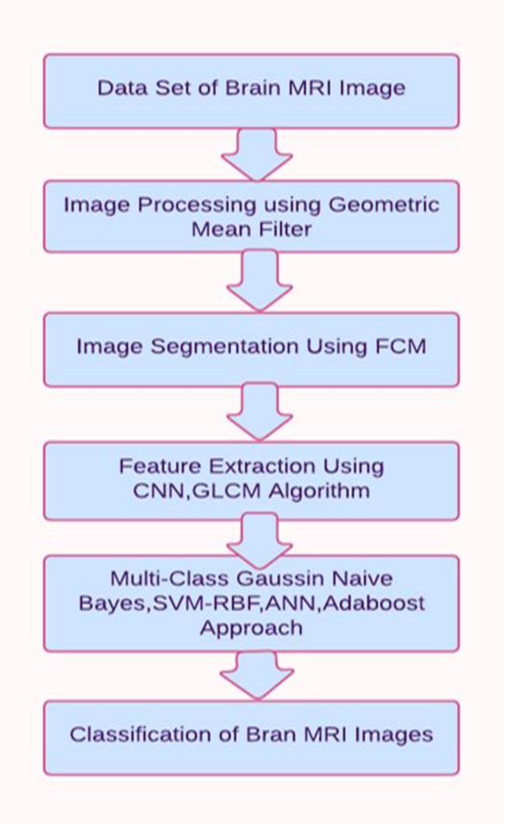

Fig 4: A schematic representation of the suggested approach

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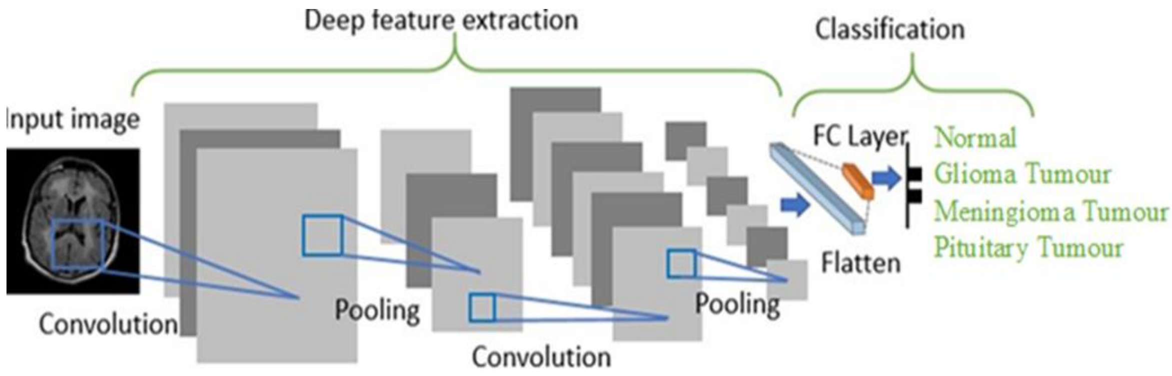

Figure 5: Convolutional neural network architecture [18].

It is made up of the following three parts: a convolutional layer to learn about both temporal as well as spatial features, a subsampling (max-pooling) layer to decrease the dimensions of a source image, as well as a fully connected (FC) layer to classify the source image into different class categories are the three layers. a typical deep learning approach using CNN to predict the outcomes, as represented in Fig. 5

This section describes deep learning as well as medically enabled multimodal for segmenting and categorizing brain tumors utilising MRI images. Noise can be seen in MRI images. In order to reduce noise from images throughout pre-processing, the geometric mean filter is utilised. Segmentation is the procedure of splitting a source image into smaller pieces using fuzzy c-means techniques. Detection of a particular area of interest is made simpler by segmentation. GLCM approach is employed to retrieve features from images; the images are then categorised utilising different ML techniques, such as CNN, SVM with RBF, Gaussian NB, ANN, as well as Adaptive Boosting. The process of dimensionality reduction is carried out using the GLCM approach. Figure 2 represents the model.

Through image pre-processing, diseases visible in images can be more precisely categorised. In MRI scans, noise appears to be the most common type of image artifact that can be seen, but there are many other types that can also be seen. These artifacts can be removed from the image by using a variety of unique image-filtering filtering techniques. Each image has a filter applied to it that makes use of the geometric mean in order to lower the noise levels [19].

B. Fully Connected Layer

The traditional DL approach can specify the loss function of neural networks that work with an FC layer to determine the loss., which refers to the estimation error of neural network. As part of a process of training, the neural network's weights need to be updated, the gradients are calculated using the loss. The most prevalent loss function for CN networks as well as various neural networks that we are utilising is the cross-entropy loss technique, in the training phase of the FC classifier. To determine the model parameters, it determines the loss between both the ground-truth label and soft target evaluated from the softmax method in the following manner:

$$L(x,y) = \sum_{i=0}^{N} - x_i \, log(\frac{y_i}{\Sigma_j \exp(y_i)}) \qquad (1)$$

where x is a on 1-hot encoded variable that presents the ground-truth label of the training set as 1 with the remaining elements as 0, and M is a total number of classes, for instance, y_i is the logit, indicating the result of the system's end layer for the i-th class of data.

C. GLCM

It is possible to decrease the dimensions from a set of feature subgroups that are deemed to be unnecessary or insignificant by using a technique called feature extraction, which belongs to the field of the processing of images. The GLCM approach is required when it's necessary to maintain links among pixels as well as restore texture properties. Calculating the co-occurrence measures of the different grey levels is a method of achieving this.

The conditional density functions of probability known as pIj|d and s are used to construct the GLM. Once the GLM is constructed, it is evaluated utilising the distances d ranging from 1 to 5 times the desired direction (\theta=0, 45, 90, and 135). For this to happen, the GLCM approach is utilised. You can find out the distance among the samples, the probability of the 2 pixels with a similar grey level (I and j) are geographically linked (d), the inter-sample distance (d as well as s), and more by utilising the calculation p(i, j|d and \theta). Correlation, entropy, contrast, as well as homogeneity represent some of the fundamental aspects of the general linear correspondence that make up the broad theory of relativity [20].

D. Ada Boost

Adaptive Boosting (AdaBoost) is a technique that can be utilised to increase the efficiency of classification outcomes generated by classifiers that aren't particularly effective. The method for assigning initial weights to each observation uses the AdaBoost approach. The classification to that which every observation belongs determines the weights that are assigned to

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it. Inaccurate classifications will eventually carry more weight after several iterations, while accurate classifications will receive very little weight as the results are repeatedly iterated. It was done in an effort to boost the classifier's effectiveness. As a result, the likelihood of inaccurate classification is diminished. Numerous children who are struggling is gradually fit in an adjustable way utilising the "boosting" procedure. In every subsequent approach, [21] of the sequence of models, more weight is placed on the knowledge that previous approaches had disregarded.

E. Artificial neural networks

ANN is frequently utilized in the field of medical to categorise medical images for the object of analysis. The ANN is similar to the human brain in so many ways, including how it goes about carrying out its tasks. By perusing a collection of previously categorised images, this is feasible to compile the information needed to form a knowledgeable evaluation of the category to which an image is related to. By perusing a group of categorised images, This is possible to achieve. Searching through a dataset of images that have been categorised into many different categories can help with this. Each image in this gallery fits into one of the categories. Artificial neurons are used to build ANNs, and each one is programmed to function similarly to biological neural systems found in the human brain. Neurons outside of the body can communicate with one another to connections. Weights may be assigned to neurons as well as edges during in the process of learning, and these weights could change in any time. in accordance with the needs of the current task. Three layers make up an ANN structure: the data input layer, the hidden layer, as well as the signal-generating outcome layer. This specific architectural design will be found in a large number of buildings. Although input, hidden, and final layers are the most popular topologies for ANN, the network can be set up in a numerous additional factor. Theoretically, One hidden layer may exist, there may be several, or there may be no hidden layers at all. Any one of these possible preferences can be realised and made a reality with enough effort The weights on the bottom level may be changed, if necessary, in order to achieve the desired results [22].

F. Support Vector Machine

offer a technique for the architecture of symbols that can distinguish among the concept of assessment held by children as well as adults [23].) The grouping challenges that SVMs encounter are succinctly outlined below: It involves both the non-direct transformation of information space to the larger determining gimmick space and the creation of the differentiating hyperplane with the most space from the goals that have the closest relationship to the training set. The SVM searches all hyperplanes that minimize preparation lapse due to the directly distinct information for the specific case which differentiates preparation information with largest separation from their closest points of isolation. the following is done In an effort to cut down on the total period of time lost throughout the preparation.

G. Gaussian NB Classifier

The ML classifier known as the Naive Bayes classifier operates under the independence assumptions between both the attributes and the classes. In the present study, The GNB classifier is one of our ML classifiers for classifying tumors of the brain [18]. The conditioned probability P(x|Y) in the Gaussian NB classifier is determined from the total of specific condition probabilities under the naive independence presumption as described in the following:

$$P(x/Y) = \frac{P(x)P(Y/x)}{P(Y)} = \frac{P(x)\prod_{i=1}^{n}.(P(y_i/x)}{P(Y)} \qquad (2)$$

Where Y is a given set of data instances (which are obtained from deep features of brain MRI) that is defined by its feature vector $(y_i, \ldots y_n)$, and X is a class focused on (kind of tumor) with classes (healthy & diseased) for different MRI set of data, Given that P(Y) is constant, the instance of information can be classified as described below:

$$x = arg\ max\ P(x)\prod_{i=1}^{n}.P(y_i/x) \qquad (3)$$

where y_i/x is measured utilizing the following formula under the assumption that features are likely to be Gaussian:

$$P(y_i/x) = \frac{1}{\sqrt{2\pi\sigma_x^2}}\exp(y_i - \mu_x/2\sigma_x^2) \qquad (4)$$

where the maximum likelihood is used to estimate the parameters μ_x and σ_x.

The smoothing variable in this study is set to 10^{-9}, the percentage of the larger variance among all the features which is given to variances for measure stability, as well as the standard parameter of the scikit-learn ML library.

Tools Used: The suggested deep neural network framework is trained using Python, and an I Core i7 4800MQ CPU running at 4.9 GHz, Nvidia GeForce RTX 4070.

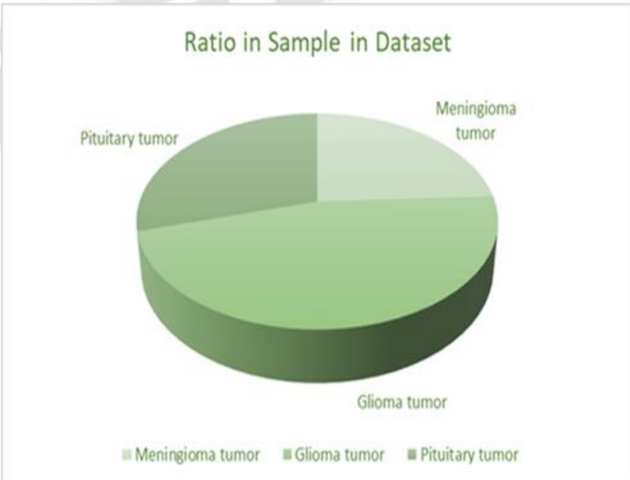

Fig. 6: Proportions in the sample dataset

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IV. MEASURES FOR EVALUATION

Accuracy, precision, recall, as well as F1-score, were used to assess the model's performance towards each of the various classes that comprise the various types of brain tumors.

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \quad (5)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (6)$$

$$Precisian = \frac{TP}{TP+FP} \quad (7)$$

$$F1 - score = \frac{2TP}{2TP+FP+FN} \quad (8)$$

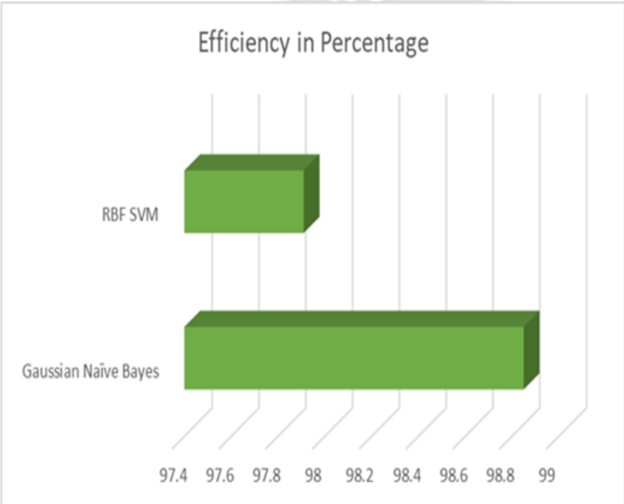

Fig.7: Evaluation of the accuracy of classifiers to detect brain tumours

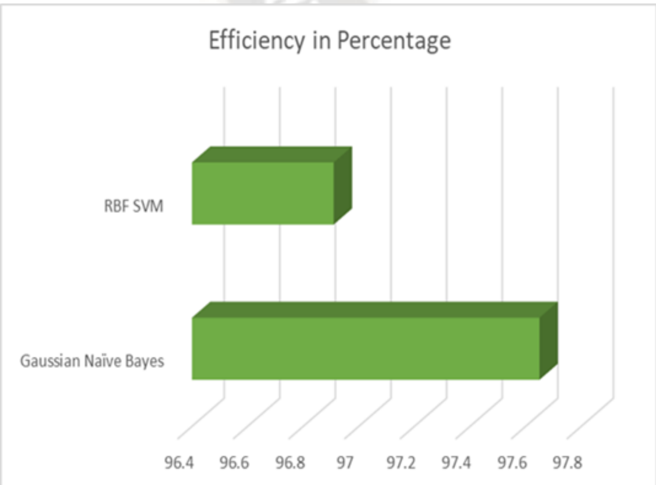

Fig. 8: Evaluation of the Sensitivity of classifiers to detect brain tumors

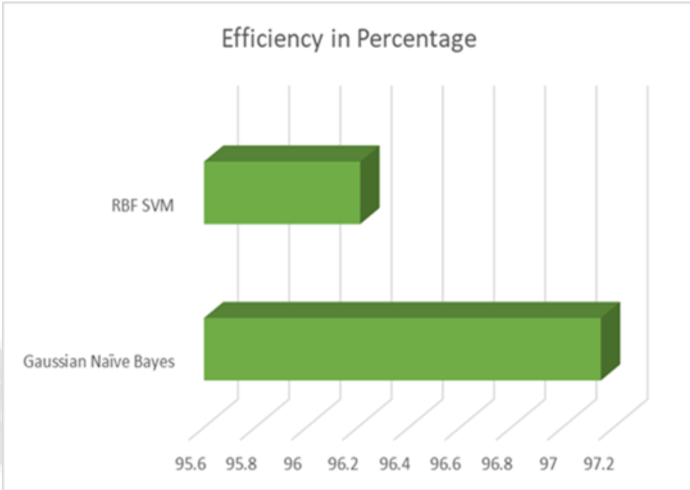

Fig.9 Evaluation of the F1 score of classifiers to detect brain tumors

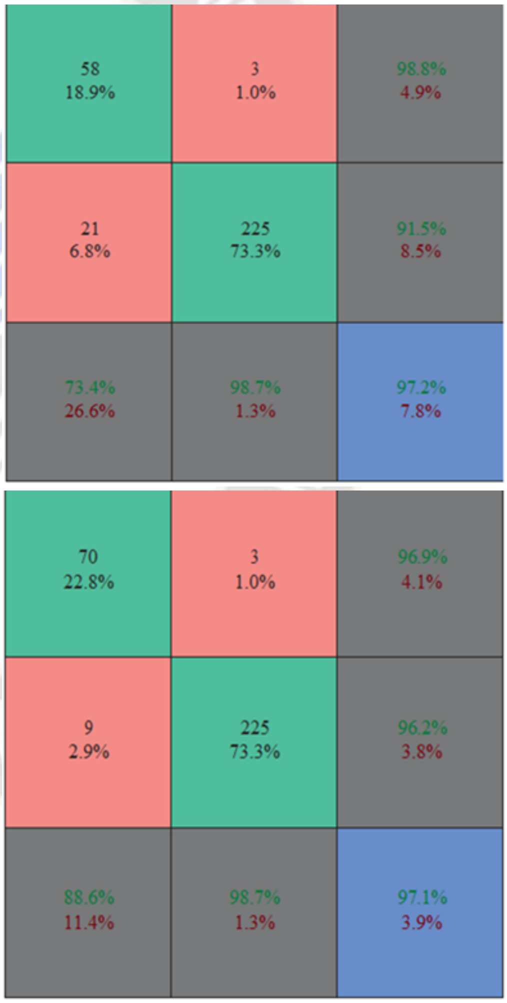

Fig.10: Confusion matrix of the suggested (a)Gaussian NB (b)RBF SVN

V. RESULT AND DISCUSSION

Two Thousand images from Ref. [24] were arbitrarily selected for this study's objectives. The remaining 3000 images are all

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healthy as well as unaffected, whereas only 1000 of them have tumors. An initial dataset of 3200 images are employed to train the model, as well as an additional 800 images are utilized for testing. For the purpose of removing noise from images, As part of the pre-processing, the GMF is utilised. In order to segment an image into smaller parts, fuzzy c-means algorithms are used. Segmentation facilitates the identification of a targeted area. The GLCM is utilised to carry out the dimensional reduction process. When extracting features from images, GLCM approach is utilised. Different machine learning techniques, such as SVM, are then used to categorise the images.

In the framework of this study, a wide range of ML methodologies are analysed as well as compared in form of how much accuracy, sensitivity, and F1-score they obtain. The outcomes of approach classification are shown in Figures 6, 7, and 8. The SVM with Gaussian NB classifier has an unmatched level of accuracy as well as F1-Score when it comes to classifying brain tumours that is unmatched by any other approach.

Table 1. Comparison of the suggested approach to earlier related research.

S.No.	Approach	Accuracy in %	Types of Classification	Techniques of Classification
1	M. G. Ertosun et al. [25]	71.0	Multi-Class	CNN
2	E. I. Zacharaki et al. [26]	88.0	Binary-Class	SVM, KNN
3	P. Afshar et al. [27]	90.89	Multi-Class	CNN
4	J.S. Paul et al. [28]	91.43	Multi-Class	CNN
5	A.H. Khan et al. [11]	92.13	Binary-Class	HDL2BT
6	A.K. Anaraki et al. [29]	94.20	Multi-Class	GA-CNN
7	Z. Huang et al [30]	95.50	Multi-Class	DCNN
8	A. Ali Ari et al. [31]	97.20	Multi-Class	ELM-LRF
9	E.S.A. EL-Dahshan et al. [32]	98.0	Binary-Class	ANN, KNN
10	Proposed Work	98.80	Multi-Class	GNB, RBF SVM

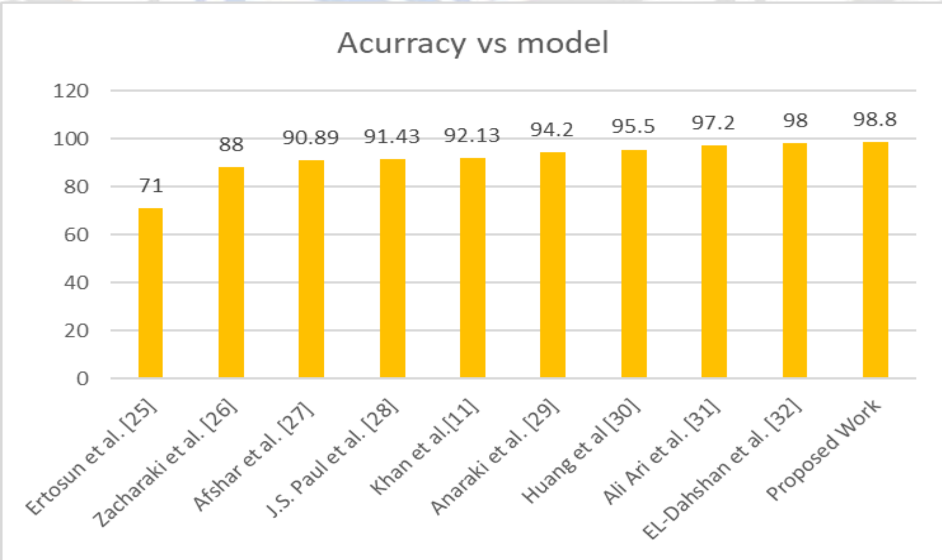

Fig.10: A Comparison graph of the suggested approach to earlier related research.

VI. CONCLUSION

Brain tumours can occasionally arise from the abnormal but also an uncontrolled proliferation of brain cells. Most patients with cancer die from brain tumors as their primary reason of death. Because of this, finding a treatment that works for a particular kind of brain tumor is becoming more difficult. Using a regular MRI scan, it is possible to create an image in three dimensions of the human brain. The purpose of this organization of research work is to investigate, identify, and classify, as well as diagnose a variety of neurological diseases. Cancer patients frequently receive radiation therapy, in order to direct radiation therapy, MRI segmentation is frequently used

.As an outcome, we can evaluate whether a tumor is present in a fragment that was picked up by an MRI. This research demonstrates a machine learning as well as medically enabled multimodal for segmenting and categorising brain tumors utilising MRI scans. Noise is present in MRI images. To help with the removal of noise during image pre-processing, the GMF is employed. The methods utilise to segment an image into smaller pieces are fuzzy c-means techniques. Segmentation helps make it simpler to identify an area of interest. The process of feature reduction is carried out using the GLCM. Digital image features are extracted using the GLCM technique. Following that, the pictures are categorized using a variety of machine-learning techniques, which include CNN, SVM, RBF, ANN, Gaussian NB classifier as well as AdaBoost are a few examples. Gaussian naïve Bayes is superior for MRI-based brain tumour detection.

Data accessibility

the information must be made obtainable upon demand.

Conflicts of Interest

The authors state that they have no conflicts of interest.

Acknowledgment

This investigation was self-funded.

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International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
DOI: https://doi.org/10.17762/ijritcc.v11i10.8427
***Article Received:** 22 July 2023 **Revised:** 10 September 2023 **Accepted:** 26 September 2023*

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