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A Convolutional Deep Neural Network Based Brain TumorDiagnoses Using Clustered Image and Feature-Supported Classifier (CIFC)Technique.

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HIGHLIGHTS

- Medical image analysis research has been performed to aid in the detection of malignant brain tumors.
- OSFC, OSIC and CIFC performed well and produced better results in classification.
- The performance metric outcome of the proposed system is 99.76% of sensitivity, 98.04% of specificity and 99.87% of accuracy.

Abstract: The recognizing and categorizing of a glioma brain tumor is a challenging task in the medical domain, and earlier identification of malignancy is much essential in order to increase the patient lifespan. Medical image analysis research has been performed to aid in the detection of malignant brain tumors. To achieve high classification performance, extracted features must be both descriptive and discriminatory. Machine learning is crucial in categorization due to its flexibility and adaptability to different problems. We have proposed a clustered image and feature-supported classifier (CIFC) along with a deep convolutional neural network framework in order to classify the brain tumor image. The proposed model consists of various classifiers such as; (i) original and segmented image feature-supported classifiers; (ii) original and segmented image-supported classifiers and (iii) clustered image and feature-supported classifiers. The free and open-access image dataset BRATS 2021 is used to train and test the proposed system framework for the tumor detection. The CFIC outperforms almost every classifier that has been proposed thus far. The performance metric outcome of the proposed system is 99.76% of sensitivity, 98.04% of specificity and 99.87% of accuracy significantly. Hence, the proposed system outcome performs well in terms of tumor detection when compared with other existing techniques.

Keywords: Glioma brain tumour; Malignancy; Deep convolutional neural network; Clustered image and feature supported classifier; Image segmentation.

INTRODUCTION

The people living styles and their general health condition needed to be monitored, and the frequent self-health care system data that has to be updated and collected at regular intervals of time. In this manner, quick and precise analysis is of preeminent importance. There has been consistent development in the clinical instrumentation field in recent years. The approach of computer-based, precise transformation of information analysis and estimations has prompted tremendous improvement [1]. Computerized scientific devices have turned into extraordinary assistance to clinical specialists in all directions. It is considered a quick developing exploration in modern research regions. Image processing is one of the significant methods in determination, where grouping is a vital cycle to characterize the sickness, whether it is benign or malignant [2]. Effective treatment of illnesses relies to a great extent upon early discovery and precise evaluation of the condition of the sickness. Disease finding is a significant process in the preservation of worldwide prosperity [3]. The present method includes estimation, investigation, and independent direction and computerized tools are important in the field of medicine. Among the deadly infections, brain tumor growth is especially worrying because of the fact that it isn't normally distinguished until it is past the point because of a delay in prognosis. Magnetic resonance image is centered explicitly because of its viability and is undisruptive [4]. Brain tumor categorization is essential for treatment planning and the cancer assessment process as a whole. Proposed system is used to examine the six various classification methods to identify brain tumor images by features. One of the deep learning techniques used in our proposed framework namely called neural network architecture in order to group the pixels and to make the graphical illustration, obtaining the essential data by selecting the input for a deep neural network [5]. The contribution of the input selection is used to avoid the over fitting issue and diminish the computational complexity effectively. The features of total spatial intensity and local accuracy are referred to as a significant portion of the proposed system framework. The proposed methodology outcome system is examined by consuming different performance metrics like; specificity, sensitivity, and accuracy. However, a clustered image and feature-supported classifier (CIFC) along with a deep convolutional neural network framework performs more efficiently than the other traditional classification techniques. The proposed system framework is organized as; literature overview is used to discuss the different image classification techniques, then the different types of classifiers are discussed, examined and the outcomes are compared with the proposed technique, and finally the conclusion and future work are done.

LITERATURE OVERVIEW

In current days, really taking a look at a large number of MRI pictures and finding brain cancer physically by a human is an exceptionally drawn-out and erroneous errand. It can influence the appropriate clinical treatment of the patient. Once more, it tends to be a tremendously tedious errand as it includes an immense number of picture datasets [6]. There is decent comparability between ordinary tissue and brain growth cells for all intents and purposes, so the division of cancer locales becomes a troublesome undertaking to do. Hence, there is a need for good and automated brain tumour detection techniques.Image modification is quite possibly the most requesting and promising field nowadays [7]. Plant strange cell development in the human brain region and the growth can be named benign (non-malignant) and deadly (carcinogenic). The last phase of the growth is utilized for manual assessment by a specialist and it takes more time and once in a while obtains adverse outcomes [8]. Today different computerized apparatuses are being utilized in the clinical field. These devices give a fast and clear outcome. The magnetic resonance image is the most broadly utilized imaging strategy to investigate the inside construction of the human body and is even used to analyze the most serious disease of clinical science, for example, cerebrum tissue [9]. The most common way of distinguishing a growth in the cerebrum comprises image processing methods that incorporate four phases.A conclusive determination of a brain cancer is fundamental for improving therapy achievement and patient endurance. Be that as it may, it is hard to physically assess numerous magnetic resonance images created in a scan center [10]. Accordingly, more exact computerized cancer identification strategies are required. As of late, numerous endeavours have examined on old style machine learning techniques to automate this cycle. The drastic improvements found in deep learning for the purpose of diagnosing brain cancers all the more precisely and effectively [11]. The objective of this concentrate consequently is to utilize brain MRI images to recognize well and illness patients. Subsequently, an improved convolutional-neural network (CNN) is created in this paper for precise cerebrum image characterization. The upgraded CNN structure is made out of parts for highlight extraction and ideal order. Nonlinear Lévy Chaotic Moth Flame Analyzer enhances hyperparameters for preparing CNN-layers. The suggested model is tested and compared to other forms of progress using the BRATS 2017 data set and brain imaging databases from Harvard Medical School [12].The brain cancer is considered as the most dangerous threat among others. Yet, presently, detection of tumor is become further developed due to the many machine learning methods. The magnetic resonance imaging is the best method among all the image handling procedures which checks the human body and gives an unmistakable outcome of the growths in a superior quality image [13]. The magnetic and radio wave images are developed by magnetic resonance image. The significant area of image segmentation is used to maintain the precision in medical domain images. Improved results are obtained by magnetic resonance images than CT image [14]. The computerized brain tumor detection provides good outcome and consists large amount of input data. The convolutional neural network produces a significant outcome in clinical field and computerized vision and used to distinguishing the brain tumor grades. The conversion of normal image to grey scale image is done by pre-processing where it has equal intensity value, however in MRI, RGB content is incorporated. The filters are utilized to eliminate the undesirable noise utilizing middle and high pass channel for good images [15].A brain growthis the tenth driving justification for the death which is normal among the people. There are several kinds of cancer that vary in presentation based on factors such as surface, location, and form, and everyone has extremely poor survival odds[16]. The wrong characterization can prompt the more regrettable results. Accordingly, these must be appropriately partitioned into the many classes or grades, which is where multiclass grouping becomes possibly the most important factor [17].

Imaging using magnetic resonance is now the most effective method or approach for examining the human brain in order to differentiate between the various growths. Convolutional neural network is the most widely used and greater scientific method that has been regarded as best in this space, and as a result, it is utilized for the benefits typically results displayed in this paper [18]. Extreme steps have been taken to improve image clustering technology, and these improvements are now being used to solve the networks order problem. The proposed model was able to divide the brain image into four different groups. To be clear, "no growth" means that the MRI of the brain does not show cancer, meningioma, pituitary growth, or glioma. "Pituitary growth" and "glioma" are the other two "growths." [19]. Brain tumors are seen as a very serious and dangerous illness. In this way, it is important for the treatment process to find the tumor quickly. Deep learning has helped a lot with clinical diagnosis in the health care industry. Convolutional neural networks have been used as a serious deep learning method to find brain tumors using magnetic resonance images [20].Deep learning algorithms and CNNs should be made better because they only have a small amount of data to work with. Since then, data augmentation has become one of the most successful ways to improve model execution. This paper gives a clear overview of the different CNN designs, including the pros and cons of ResNet, AlexNet, VGG16, and VGG19. From that point onward, we give a productive technique to identifying the brain cancers utilizing MRI datasets in light of CNN and information expansion [21].The brain cancer is treated as a contorted tissue and the cells are recreated quickly and endlessly, and it doesn’t have a control of cancer development. Deep learning has been contended to can possibly conquer the difficulties related with identifying and mediating in the brain tumor [22]. It is deeply grounded that the division strategy can be utilized to eliminate strange growth areas from the brain, as this is one of the high-level technological organization and identification instruments. On account of brain growths, early infection location can be accomplished really utilizing dependable high level artificial intelligence mechanism with neural network algorithms [23]. This study intended to basically investigate the proposed framework, utilize the visual geometry group 16 for finding brain cancer growths, execute a convolutional neural network model structure, and set boundaries to prepare the model for this test. Visual geometry group is utilized as one of the greatest performing convolutional neural network models due to its effortlessness [24]. Besides, the review fostered a viable way to deal with recognize brain cancer growths utilizing MRI to support making fast, effective, and accurate choices.Brain cancer is seen as a disease that can kill you. It happens when strange cells grow in the brain parenchyma. So, if this disease is found early and in the right place, it can save a patient's life [25]. This paper suggests a new way to use magnetic resonance images to find out if someone has brain cancer. The suggested system framework uses a FCNNand domain adaptation. The proposed system has five phases which are pre-processing, skull-stripping, convolutional neural network-based cancer division, post processing, and transfer learning-based brain cancer growth categorization [26]. The magnetic resonance pictures are sifted to dispense with the noise and are work on the differentiation in the preprocessing. For division of brain cancer pictures, the proposed convolutional neural network model is utilized, and for post processing, the worldwide limit procedure is used to dispose of little non tumor locales that upgraded division results [27].

Brain tumors are caused by the growth of strange cells in the brain, which can lead to disease. Magnetic resonance imaging assessment is the standard way to spot the growth of brain cancer. The strange growth of tissue in the cerebrum can be seen in the MR images. From the survey study, machine and deep learning methods are used to find out how brain cancer grows. Whenever these techniques are used on MRI images, the growth of brain cancer can be found much faster and with more accuracy, which helps the patient get the right treatment and the doctor make the right decision [28]. In the presented design, a self-characterized ANN and a CNN were used to study brain cancer and look at their properties.The brain tumour automatic detection is much essential for human lives and the image classification and segmentation is the important key factor for magnetic resonance image analysis [29]. The deep learning methods are more efficient but the processing time is higher than the usual since it has a more layers. So, it may not be convenient for lower dataset operations. The proposed system consists of a smaller number of layers and less complexity in order to address the abnormality in brain region. The malignant portions are classified and labelled by the proposed system from the overall dataset images. However, the proposed system outcome is superior to the other existing CNN techniques [30].The creation of a reliable automated diagnostic technique is required to increase the accuracy of tumor identification. Researchers created a range of segmentation algorithms to accurately classify brain tumors. One of the most difficult tasks in medical image processing is generally acknowledged to be segmenting brain images. An innovative automated detection and classification method was put forth in this article. Pre-processing MRI images, segmenting images, extracting features, and classifying images were just a few of the phases that made up the suggested method. Background noise was removed using an adaptive filter during the pre-processing stage of an MRI scan. The local-binary grey level co-occurrence matrix (LBGLCM) was used for feature extraction, and enhanced fuzzy c-means clustering (EFCMC) was used for image segmentation. After extracting the scan features, we used a deep learning model to divide MRI images into two categories: glioma and normal. In order to create the classifications, a convolutional recurrent neural network (CRNN) was used [31]. There are numerous ways to classify brain tumors. One common classification type, for instance, is to separate brain tumors into benign and malignant tumors. Typically, benign brain tumors form inside the skull but outside of the brain tissue. An important component of this group is meningiomas. Contrary to benign tumors in other organs, brain tumors can occasionally result in conditions that are life-threatening. Meningiomas, for instance, may sporadically develop into cancerous tumors. They have a good chance of being removed by surgery because they typically do not spread to the surrounding brain tissue. Pituitary tumors are tumors that begin in the pituitary glands, which regulate hormones and other bodily processes. The benign tumors known as pituitary tumors do not spread to other body parts [32]. With the advancement of medical imaging, imaging techniques can now give doctors a clear picture of the human brain's structure and play a significant role in the diagnosis and evaluation of brain tumor treatments. These imaging methods can help doctors make a precise diagnosis and create a treatment strategy by providing details on the location, size, and shape of brain tumors. In neurology, magnetic resonance imaging (MR) is one of the most frequently used scanning techniques. In order to create an image of the interior of the target tissue, radiofrequency signals are used to excite the tissue under the influence of a very strong magnetic field. High soft tissue contrast and no ionizing radiation exposure are two benefits [33]. Oncologists typically use medical imaging techniques like computed tomography (CT) scans and magnetic resonance imaging (MRI) to perform the initial evaluation of brain tumors. The brain structure can be seen in great detail using these two modalities, and any changes can be seen. However, a surgical biopsy of the suspected tissue (tumor) is required for a thorough diagnosis by the specialist if the doctor suspects a brain tumor and they need more information about its type. These various imaging techniques for brain tissue have improved recently in terms of image contrast and resolution enhancement, enabling radiologists to detect even small lesions and thus increase diagnosis accuracy [34].

PROPOSED SYSTEM FRAMEWORK

The malignant portion of the brain region can be addressed from the MR images with the help of image classification method, and it provides the classified outcome like; benign or glioma. The free open access BRATS 2021 image dataset has been used in this research work. The two balancing qualities and features extractions are needed like; involvement and distinction in order to maintain the précised performance outcome of the classification. Classification in machine learning is considered as difficult since it has a wide range of approaches and appropriateness for the issue.There are two distinct subsets of each brain tumordataset used for development and evaluation purposes. The data set is classified into an 80% training set and a 20% testing set. The deep learning toolbox is used in MATLAB R2019b for the simulation.

Deep Convolutional Neural Network

The DCNN is one among the simple expansion of conventional artificial neural network and it has more hidden layers. The input layer is used to obtain the each image feature vectors as an input from training dataset. The bias neuron is used to augment the input layer by adding +1 as constant bias signal for feature of the each vector. The features signal is distributed in the input layer by the neuron to the entire first hidden layer nodes through its weight. Consequently, every neuron with the exception of bias in the first secret hidden layer calculates the weighted amount of entire information of input layer signals. The weight vector arriving at every hidden neuron is autonomous of any remaining weight vectors. However, each layer $\mathrm{a_k}$ consists of $\mathrm{R_k}$ hidden neurons, and additionally it has bias neuron too. The basic architecture of DCNN is illustrated in Figure 1. Here, $\mathrm{B^k}$ is the weight matrix and index layer of the weight vectors of the layers. And, $\mathrm{A_k}$is the connectivity of the all hidden and previous layers with the help of its weighted matrix$\mathrm{B_k}$. Here, k=1 is an indexed value for hidden layer and q is associates by its weighted matrix $\mathrm{B^k}$, and it is shown in equation (1), and the (4) shows weighted matrix equation.

$$\mathrm{net}^k_{j,\,o}=b^k_{j,\,1}y_{1,\,o}+b^k_{j,\,2}y_{2,\,o}+b^k_{j,\,3}y_{3,\,o}+\ldots+b^k_{j,R_k}y_{R_k,o}+b^k_{j,\,o} \tag{1}$$

$$\mathrm{net}^k_{j,\,o}=\sum_{a=0}^{q} b^k_{j,\,a}y_{j,\,o}\ \mathrm{net}^k_{j,o}=\sum_{a=0}^{q} b^k_{j,a}y_{j,o} \tag{2}$$

$$z^k_{j,\,o}=\begin{cases}\mathrm{net}^k_{j,\,o},\ \mathrm{ifnet}^k_{j,\,o}>0\\ \text{else (RELU)}\end{cases} z^k_{j,o}=\begin{cases}\mathrm{net}^k_{j,o},\mathrm{ifnet}^k_{j,o}>0\\ \mathrm{else(RELU)}\end{cases} \tag{3}$$

$$B^k=\begin{pmatrix} b^k_{1,0}b^k_{1,1}b^k_{1,2}b^k_{1,Rk\text{-}1}\\ b^k_{2,0}b^k_{2,1}b^k_{2,2}b^k_{2,Rk\text{-}1}\\ b^k_{3,0}b^k_{3,1}b^k_{3,2}b^k_{3,Rk\text{-}1}\end{pmatrix} \tag{4}$$

Here, k is the index layer, and j represents the j^{th} neuron in the layer, and R_k illustrates the number of neurons (hidden) in the layer, and p is the general pattern, and $b^k_{j,a}$ represents the weight associates with a^{th} neuron of the layer k-1.

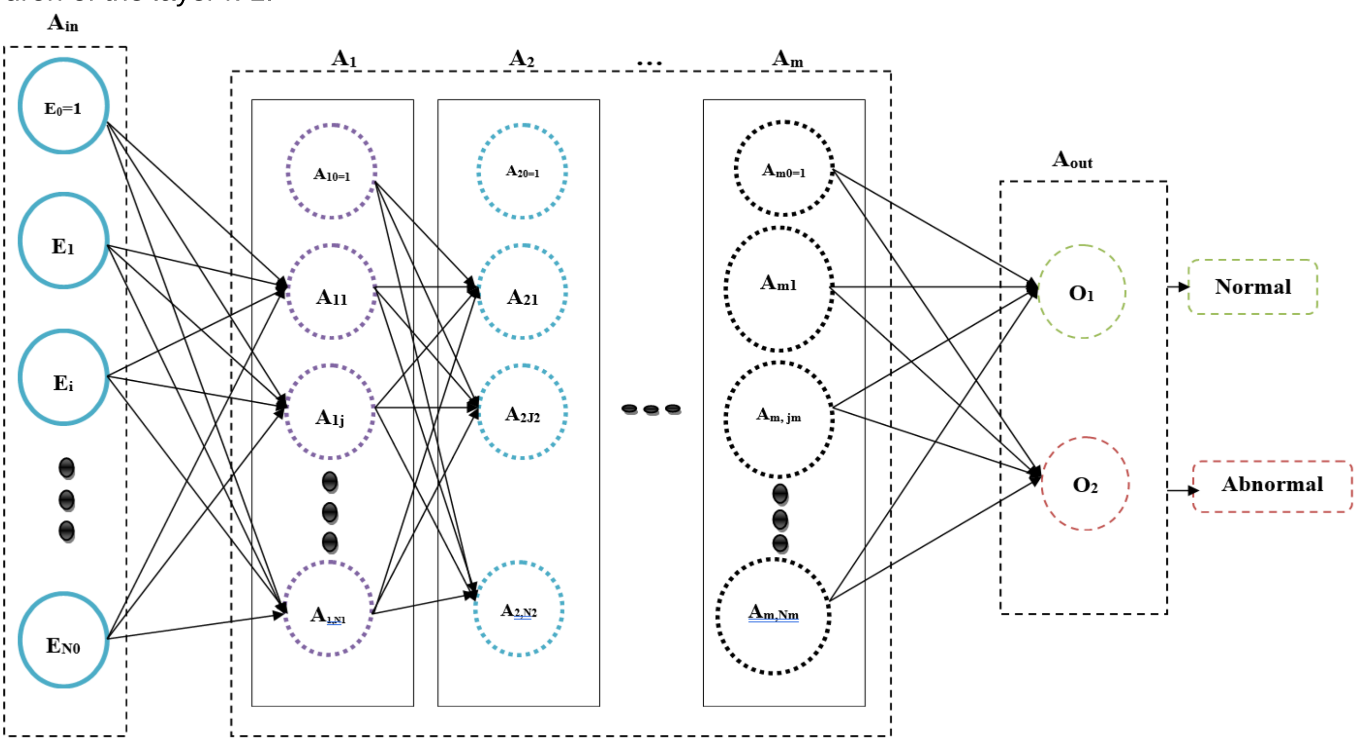

Figure 1. DCNN architecture

The outcome of the last layer (hidden) that feeds to the outcome layer A_{out}. It has two neurons and it is representing the classes of benign and malignant tumor. Here, the activation function is derived by the softmax function in the outcome layer, and it can be written as,

$$s_t=\sum_{j=0}^{Ru} b_{t,j}^{u} z_{j,o}^{u} \; s_t = \sum_{j=0}^{Ru} b_{t,j}^{u} z_{j,o}^{u} \tag{5}$$

Here, t=1 represents the malignant and t=0 represents the benign classes.

$$C_t=\text{softmax}(s_t) C_t = \text{softmax}(s_t) \tag{6}$$

$$\text{Softmax}_{s_t}=\frac{e^{s_t}}{\sum_{v=0}^{1} e^{s_v}} \; \text{Softmax}_{s_t} = \frac{e^{s_t}}{\sum_{v=0}^{1} e^{s_v}} \tag{7}$$

The cost functions cross entropy loss equation can be written as,

$$\text{Crossentropyloss}=-\sum_{t=0}^{1} f_i \log(S_t) \; \text{Crossentropyloss} = -\sum_{t=0}^{1} f_i \log(S_t) \tag{8}$$

Here, the traditional artificial neural network has been used since the proposed system uses more number of preprocessing units based on features selection, extraction and segmentation. However, the proposed system classifier is referred as a mixed version of various classifiers. Here, the multilayer perceptron is used to combine the different unit's outcome of the proposed framework. Rectified linear function is referred as the activation function of the hidden layer. Also, the softmax function is the outcome activation layer of the output layer. The classical back-propagation algorithm is used to train the classifiers in order to support the proposed system framework and to perform well.

Training, Testing and Operation of Classifiers

The proposed system framework uses the same input (data) in all the three (combined) classifiers for obtaining outcomes.However, the outcome of the classifiers is almost same but it finds some deviation in data space regions. However, the weighted sum of the entire classifier outcome is complex. In order to diminish the sum squared error by using the vector weights which could be achieved by utilizing the least square fit technique.Here, the proposed system classifier has three phases like; training, testing and validating. Figure2, 3, 4 depicts the training, testing and operation phases of the classifier.

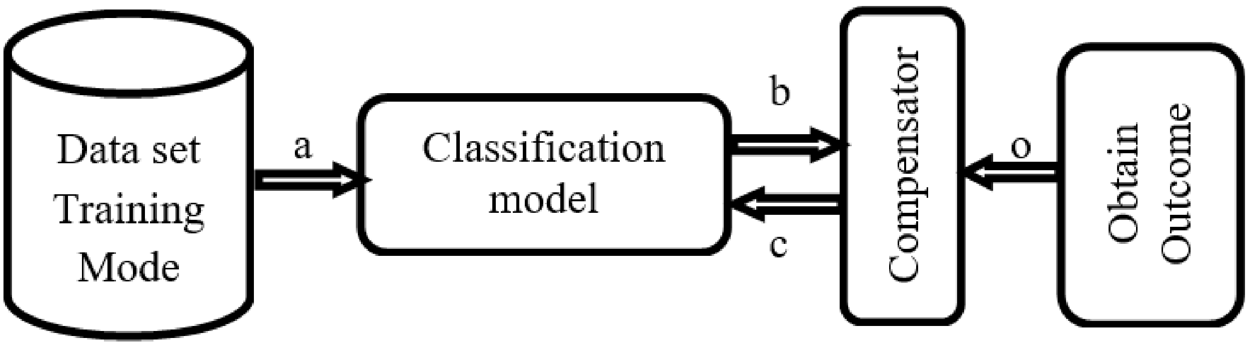

Figure2. Training phase of the classifier

Algorithm 1: P Training Phase

Start

Step 1:All the biases and corresponding weightsto the respective layers are computerized to small random units.

Step 2:Move forward the computed values.

Step 3:Apply back-propagation algorithm in order to make the weight adaptation.

Step 4:Apply advance ending criteria to terminate.

Stop

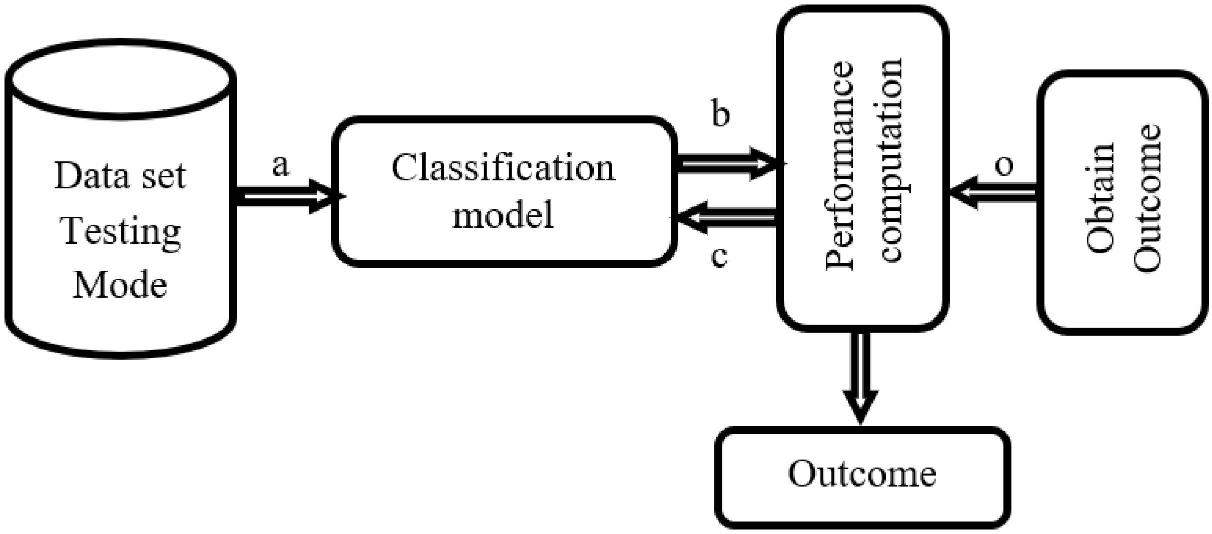

Figure 3. Testing phase of the classifier

Algorithm 2 – Testing Phase

Start
Step1: Dataset for testing is applied to the already trained framework.
Step 2:The outcome b is expected to obtain.
Step 3:The parameters like; sensitivity, accuracy and specificity is computed by using b and o.
Stop

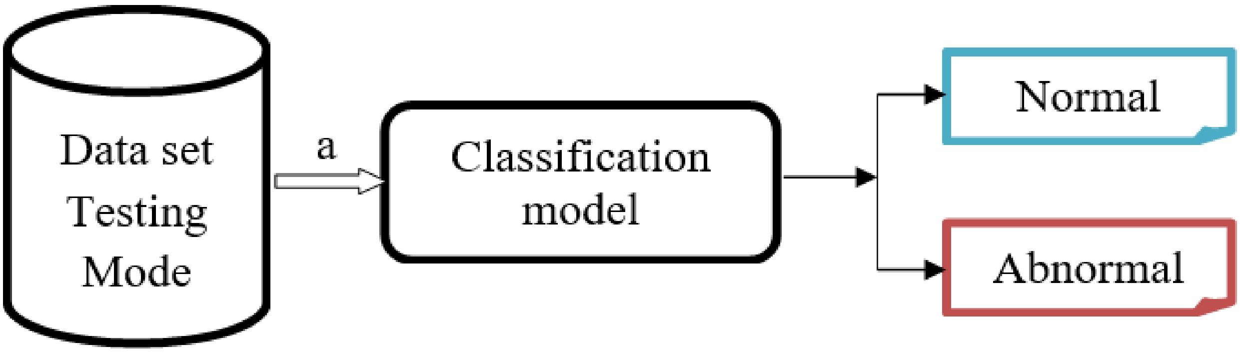

Figure 4. Operation phase of the classifier

Algorithm 3 – Operation Phase
Start
Step 1:The query image (unknown) Ur is applied to the fully-evaluated framework.
Step 2:Calculate the Gr for reference image Ur.
Step 3:Return the Gr as expected outcome.
Stop

Various Classification Method of Brain Tumor

Depending on the situation and what needs to be done, there are two main ways to classify images: image-based classifications and feature-based classifications. The image supported classification uses multi-layered architecture (hidden layers) based on the feature selection for obtaining classification accuracy. The resultant of the output layer is a classified outcome of the feature vectors and it is combined with output of the classifier. The feature supported classification is used to derive the feature from the each input image of the classifier. However, each feature are derived and extracted in terms of computationally, precisely and symmetrically based on the image characteristics and properties such as; location of pixel, intensity of pixel and color. The process of feature selection is used to choose the least set of appropriate and adequate features to the existing issue. The proposed model consists of various classifiers such as; (i) original and segmented image feature-supported classifiers (OSFC); (ii) original and segmented image-supported classifiers (OSIC) and (iii) clustered image and feature-supported classifier (CIFC). Figure 5, depicts the graphical illustration of original image and segmented image feature supported classifiers. Table 1 illustrates the Performance metrics of Original and segmented image feature supported classifiers with various training/testing ratios and the bettermetric outcome is observed for the ratio of 70:30 with values 98.37% of sensitivity, 89.9% of specificity, and 97.13% of accuracy respectively.

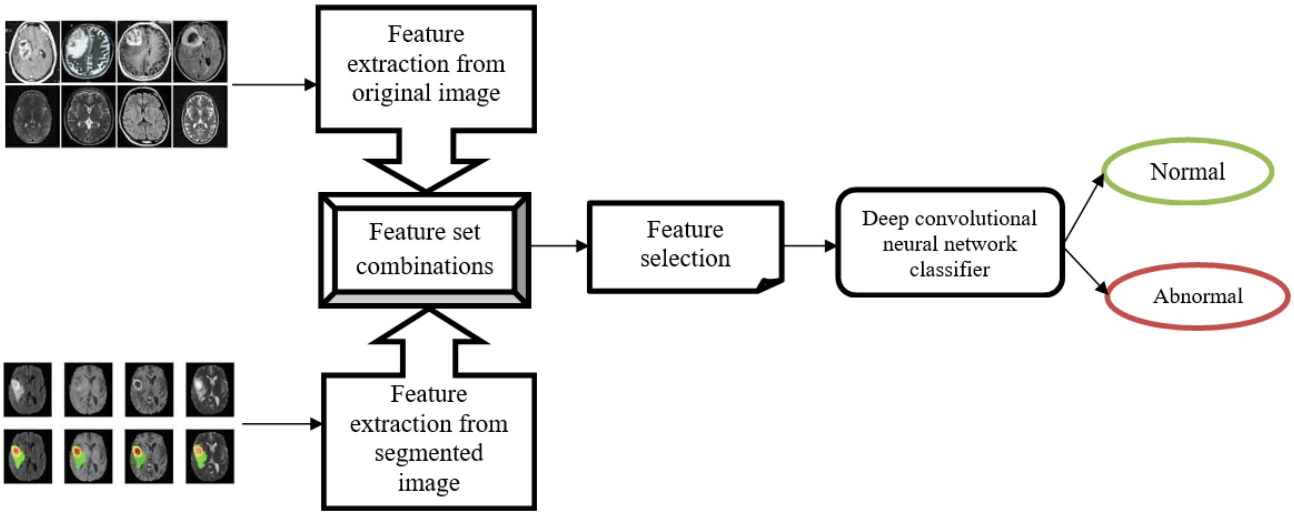

Figure 5. Original and segmented image feature supported classifiers

Table 1. Performance metrics of original and segmented image feature supported classifiers with various training/testing ratio.

Training / Testing ratio (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
90-10	96.47	87.9	96.4
80-20	93.05	83.52	93.06
70-30	98.37	89.9	97.13
60-40	94.9	87.93	93.47
50-50	93.66	87.53	92.25
40-60	90.8	81.4	88.58
30-70	90.06	73.6	85.32

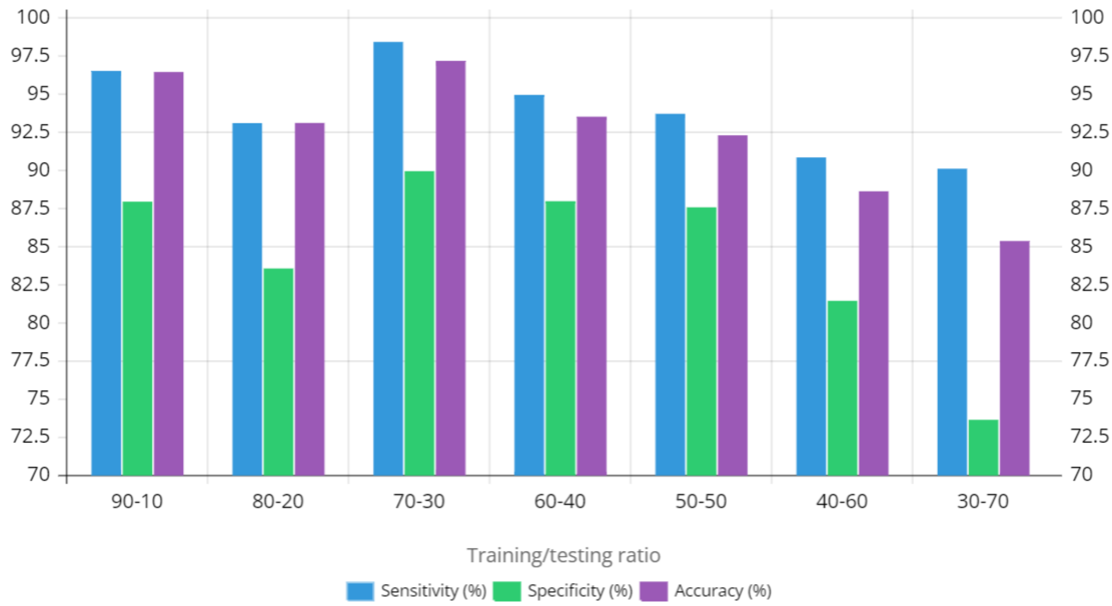

Figure 6. Graphical view of training/testing ratio of original and segmented image features

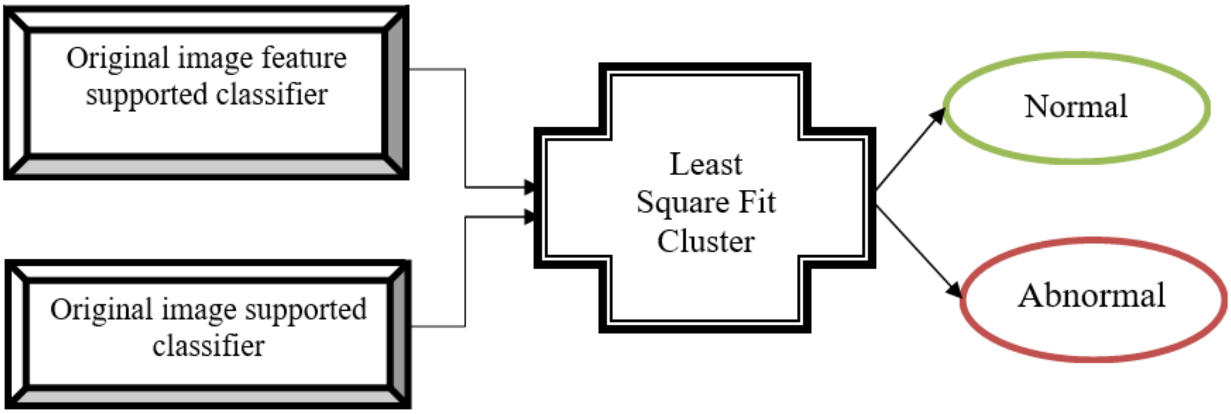

Figure 7. Original image and segmented image supported classifier

Table 2. Performance metrics of original and segmented image supported classifiers with various training/testing ratio

Training / Testing ratio (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
90-10	95.8	95.4	96.26
80-20	92.3	93.1	93.47
70-30	98.5	96.1	98.36
60-40	95.9	91.89	95.1
50-50	95.3	93.28	94.89
40-60	92.5	87.01	91.23
30-70	93.9	83.19	90.82

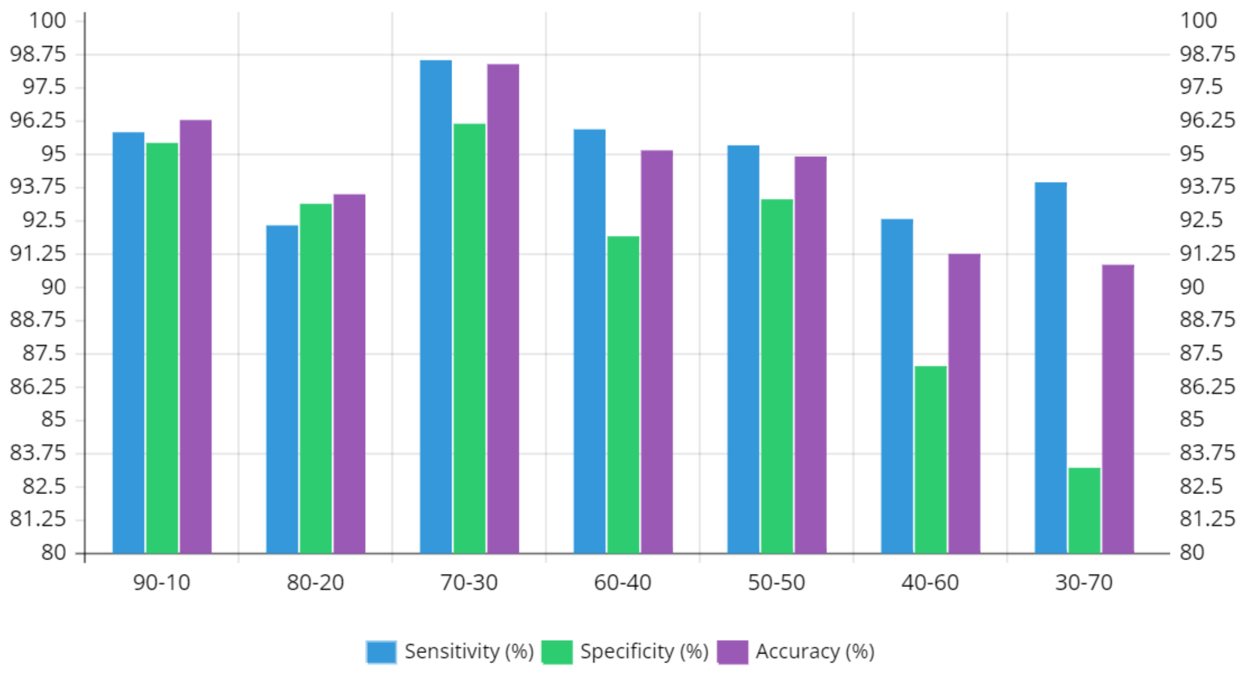

Figure 8. Metric comparison graphical illustration of original and segmented image

Figure 6, depicts the graphical view of training/testing ratio of original and segmented image features. The pre-processed magnetic resonance image classic and segmented images of the brain are utilized as the input of original image and segmented image classifier model, and the two classifiers are combined by using least square fit cluster model shown in Figure 7. The expected information of each classifier is being addressed as benign or malignant; depend on the given input images. Figure 8, illustrates the metric comparison graphical illustration of original and segmented image.

The classification based on the cluster with the least squared fit is shown in Figure 9 together with feature-supported classifiers. It provides the line that fits the given split data points the best. Along with providing the precise output of the observed image as benign or malignant, it also decreases the square of the offset values.The performance metrics of clustered image and feature supported classifiers is examined and it is shown in Table 3.

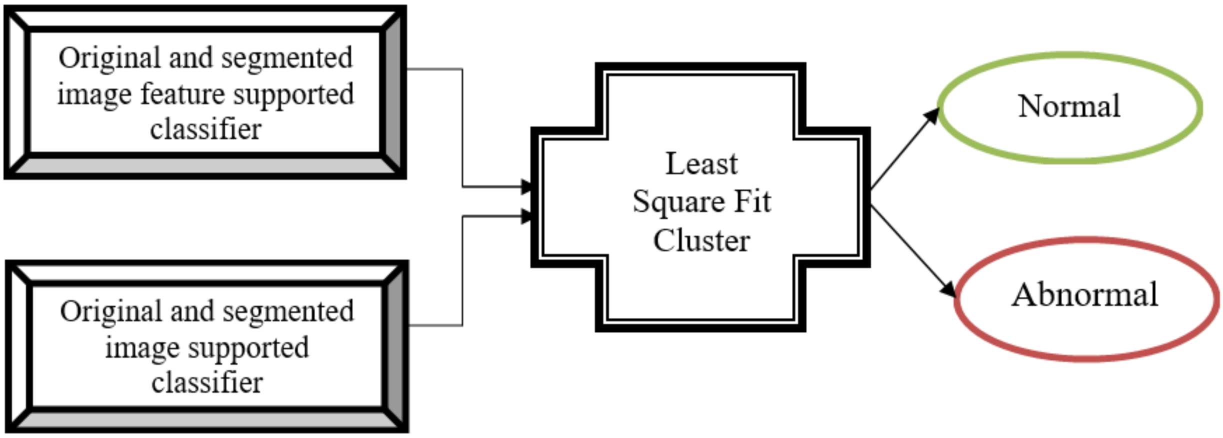

Figure 9. Clustered image and feature supported classifiers

Table 3. Performance metrics of clustered image and feature supported classifiers

Training / Testing ratio (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
90-10	97.57	97.57	96.18
80-20	94.6	96.58	93.77
70-30	99.76	98.04	99.87
60-40	96.8	94.96	96.42
50-50	96.01	95.15	95.81
40-60	93.97	91.42	93.36
30-70	94.17	83.65	91.12

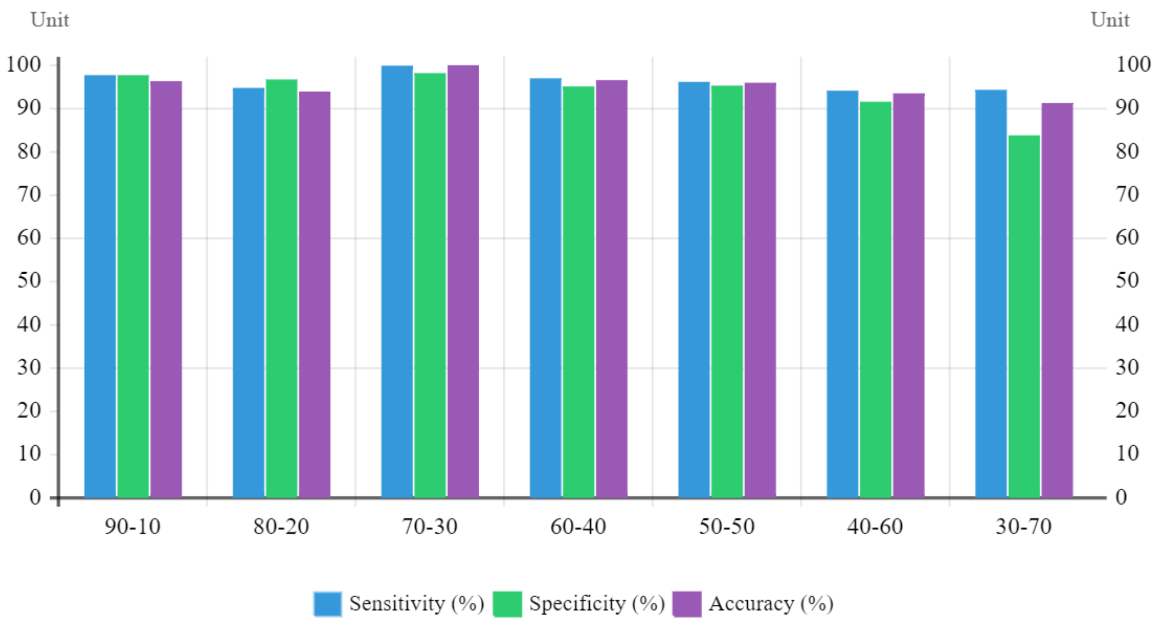

Figure 10. Graphical view of clustered image and feature-supported classifier metric comparison

Figure 10, represents the graphical view of clustered image and feature-supported classifier metric comparison. The performance outcome of the Least Square Fit Cluster (LSFC) model is shown in Table 2. The better achievement of the LSFC is observed for the ratio of 80:20 with values 98.5% of sensitivity, 96.1% of specificity, and 98.36% of accuracy respectively. The performance outcome of clustered image and feature supported classifiers is observed for the value of 70:30 that is 99.76% of sensitivity, 98.04% of specificity and 99.87% of accuracy.

RESULTS AND DISCUSSION

The BRATS-21 open access image dataset is utilized in our proposed work in order to train and validate the classifiers. The three (combinational) classifiers have been used in this work categorize the brain tumor based on the MR imaging. The performance metric calculation has been done for each classifier and the outcomes are evaluated by the respective formulas.

$$\text{Sensitivity}=\frac{\text{Truepositive}}{\text{Truepositive+Falsenegative}} \tag{9}$$

$$\text{Specificity}=\frac{\text{Truenegative}}{\text{Truenegative+Falsepositive}} \tag{10}$$

$$\text{Accuracy}=\frac{\text{Truepositive+Truenegative}}{\text{Truepositive+Falsepositive+Truenegative+Falsenegative}} \tag{11}$$

Above equations (9), (10), & (11) are the performance metric evaluation to compute the proposed system outcome. The performance metric comparison of proposed system classification techniques is examined and it is shown in Table 4.

Table 4. Proposed system different classification technique metric comparison outcome

Proposed methods(classifiers)	Sensitivity (%)	Specificity (%)	Accuracy (%)
OSFC	98.37	89.9	97.13
OSIC	98.5	96.1	98.36
CIFC	99.76	98.04	99.87

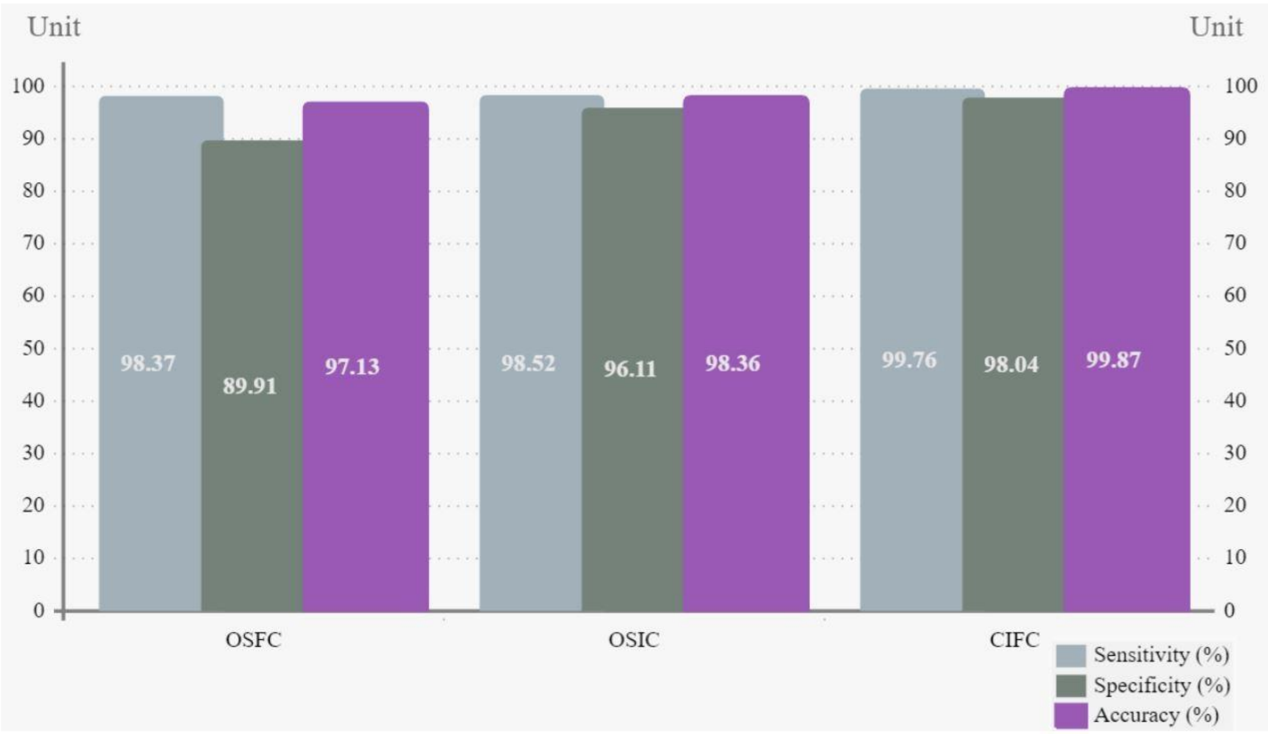

Figure 11. Performance metric graphical illustration of proposed system classifiers

Table 5. Performance comparison of proposed and existing methods metric outcome

Methods (classifiers)	Sensitivity (%)	Specificity (%)	Accuracy (%)
CIFC (proposed)	99.76	98.04	99.87
Machine learning (CNN)	97.65	96.15	98.91
Fully connected CNN	94.5	94.2	92.7
CNN	94.2	94.8	94.2
Multiplane-CNN	91.3	95.45	96.9

Table 5, illustrates the performance comparison of proposed and existing methods metric outcomes. Figure 11, depicts the graphical illustration of the proposed and existing method performance metric outcomes. Data from the Table 5 clearly indicated that the proposed CIFC method obtained better results in all aspects than the existing techniques.

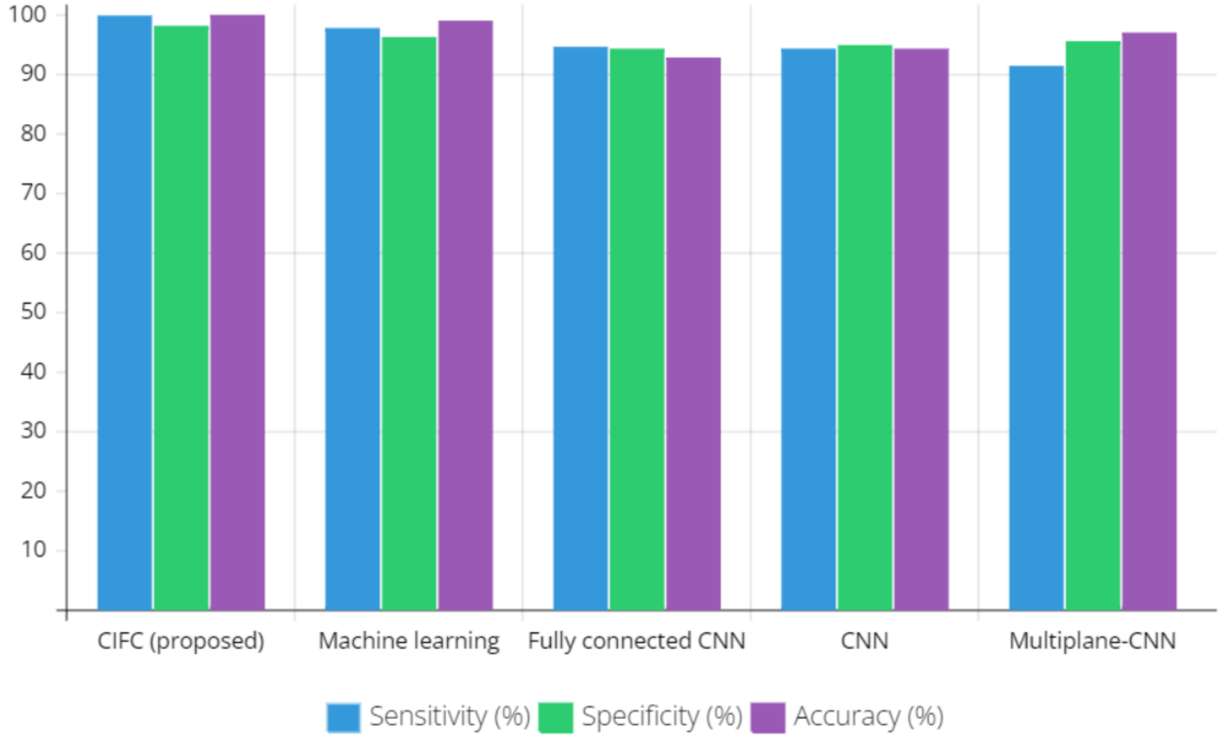

Figure 12. Proposed and existing method performance comparison

Performance Metric Comparison of Proposed and State-of-art Methods

Existing approaches for brain tumor classification are compared and summarized with the proposed method's performance is shown in Figure 12.

Accuracy, Specificity and Sensitivity Comparison of Proposed and State-of-art Methods

One metric used to evaluate performance is the precision described by equation (11). According to Table 5, the suggested CIFC scheme achieves an accuracy of 99.87%, whereas the accuracy of the next best approach, machine learning (CNN), is only 98.91%. In comparison to the closest rival, the suggested strategy is 0.96 percentage points better. The effectiveness is compared using the specificity, as described by equation (10). Table 5 demonstrates that the suggested CIFC approach achieves a higher level of specificity 98.04% than the next best method, machine learning (CNN), which achieves a score of 96.15%. As a result, the proposed strategy outperforms the closest rival by a margin of 1.89%. We employ the sensitivity measured by the coefficient in equation (9). Table 5 demonstrates that the suggested CIFC approach has a sensitivity of 99.76%, whereas the next best method, machine learning (CNN), only manages a sensitivity of 97.65%. As a result, the suggested approach outperforms the closest rival by 2.11%.

CONCLUSION AND FUTURE WORK

In order to solve the classification issue there are three combinational frameworks are examined and obtained the expected outcome at the end. The three classifiers such as; OSFC, OSIC and CIFC performed well and produced better results in classification. Based on the performance outcome from the classifiers list, the CIFC obtained better outcomes in all aspects like; 99.76% of sensitivity, 98.04% of specificity and 99.87% of accuracy than the OSIC and OSFC model. Also, the proposed CIFC outcomes are compared with the existing classification techniques like; Machine learning-CNN, fully connected CNN, classical CNN, multi plane CNN, and the comparison result shows that the proposed CIFC model is performed well than other techniques. However, the proposed system used grey scale images for classification, and in future the RGB image will be used for image classification.

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REFERENCES

1. SwarajaK,MadhaviRK, Sujatha CN, Valiveti H. Brain Tumor Classification of MRI Images Using Deep Convolutional Neural Network. Traitement du Signal.2021; 38(4):1171-9.
2. Siyu LAI, Qinghua YANG, Wenjin HE, Yuanzhong ZHU, Juan WANG. Image Retrieval Method Combining Bayes and SVM Classifier Based on Relevance Feedback with Application to Small-scale Datasets. TV-TG. 2022; 29(4): 1236-46.
3. Balaji G, Sen R, Kirty H. Detection and Classification of Brain tumors Using Deep Convolutional Neural Networks. eess.IV. 2022; 1-11.
4. Khan MSI, Rahman A, Debnath T, Karim MR, Nasir MK, Band SS, et al. Accurate brain tumor detection using deep convolutional neural network. Comput Struct Biotechnol J. 2022 Aug 27; 20:4733-45.
5. Pitchai R, Praveena K, Murugeswari P, Ashok Kumar, Mariam Bee MK, Alyami NM, et al.Region Convolutional Neural Network for Brain Tumor Segmentation. Comput Intell Neurosci. 2022; 2014:1-9.
6. Saravanan S, Kumar VV, Sarveshwaran V, Indirajithu A, Elangovan D, Allayear SM. Computational and Mathematical Methods in Medicine Glioma Brain Tumor Detection and Classification Using Convolutional Neural Network. Comput Math Methods Med. 2022 Oct 14; 2022:4380901.
7. Kavitha S, Uma Maheswari, Venkatesh R. Intelligent Intrusion Detection System using Enhanced Arithmetic Optimization Algorithm with Deep Learning Model. TV-TG. 2023; 30:1217-24
8. Amin J, Sharif M,Haldorai A, Yasmin M, Nayak RS. Brain tumor detection and classification using machine learning: a comprehensive survey. Complex Intell Syst. 2021; 8:3161–83.
9. Khan HA, Jue W,Mushtaq M, Mushtaq MU.Brain tumor classification in MRI image using convolutional neural network. Math Biosci Eng.2020; 17(5):6203-16.
10. Saeedi S, Rezayi S, Keshavarz H, R NiakanKalhori S. MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Med Inform Decis Mak. 2023 Jan 23;23(1):16.
11. Asha P, Ashwini P, Laxmibai Pooja DH,JyotiP. Brain Tumor Detection using Convolutional Neural Network. IJIRMPS. 2021; 9(4):251-4.
12. Stephe S, Jayasankar T, Vinoth Kumar K. Motor imagery recognition of EEG signal using cuckoo-search masking empirical mode decomposition. IJITEE. 2019; 8(11):2717-2720.
13. Jegannathan P,Pichumani S.Brain Tumor Detection using Convolutional Neural Network. TURCOMAT. 2022; 12(11):686-92.
14. Tiwari P, Pant B, Elarabawy MM, Abd-Elnaby M, Mohd N, Dhiman G, Sharma S. CNN Based Multiclass Brain Tumor Detection Using Medical Imaging. Comput. Intell. Neurosci. 2022 Jun 21; 2022:1830010.
15. Parameswari A, Vinoth Kumar K, Gopinath S. Thermal analysis of Alzheimer's disease prediction using random forest classification model. Mater. Today: Proc. 2022; 66(3): 815-21.
16. ZainEldin H, Gamel SA, El-KenawyEM, Alharbi AH, Khafaga DS, Ibrahim A, Talaat FM. Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness Grey Wolf Optimization. Bioeng. (Basel). 2022 Dec 22;10(1):18.
17. Saeedi S, Rezayi S, Keshavarz H, R NiakanKalhori S. MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Med. Inform. Decis. Mak. 2023 Jan 23;23(1):16.
18. Gokila Brindha P, Kavinraj M,Manivasakam P, Prasanth P. Brain tumor detection from MRI images using deep learning techniques. IOP Conf. Ser. Mater. Sci. Eng. 2021; 1055(1):012115.
19. Parameshwari K,Batri K, Saravanan S. A Comprehensive Overview and Performance Analysisof MRI Image Based Brain Tumor Segmentation and Classification Approaches. Ann. Romanian Soc. Cell Biol. 2021; 25(5):87-94.
20. Rai HM,Chatterjee K. 2D MRI image analysis and brain tumor detection using deep learning CNN model LeU-Net. Real-time 2D/ 3D Image Processing with Deep Learning. Multimed. Tools Appl. 2021; 80:36111–41.

21. Gu X, Shen Z, Xue J, Fan Y, Ni T. Brain Tumor MR Image Classification Using Convolutional Dictionary Learning With Local Constraint. Front. Neurosci. 2021 May 28; 15:679847.
22. Zhao X, Wu Y, Song G, Li Z, Zhang Y, Fan Y. A deep learning model integrating FCNNs and CRFs for brain tumor segmentation. Med. Image Anal. 2018 Jan; 43:98-111.
23. Chakrabarty S, Sotiras A, Milchenko M, LaMontagne P, Hileman M, Marcus D. MRI-based Identification and Classification of Major Intracranial Tumor Types by Using a 3D Convolutional Neural Network: A Retrospective Multi-institutional Analysis. Radiol.: Artif. Intell. 2021 Aug 11; 3(5):e200301.
24. Arabahmadi M, Farahbakhsh R, Rezazadeh J. Deep Learning for Smart Healthcare-A Survey on Brain Tumor Detection from Medical Imaging. Sensors (Basel). 2022 Mar 2; 22(5):1-27.
25. Kokila B, Devadharshini MS, Anitha A, Abisheak Sankar S.Brain Tumor Detection and Classification Using Deep Learning Techniques based on MRI Images. J. Phys. Conf. Ser.2021; 1916:012463.
26. Gao P, Shan W, Guo Y, Wang Y, Sun R, Cai J, et al. Development and Validation of a Deep Learning Model for Brain Tumor Diagnosis and Classification Using Magnetic Resonance Imaging. JAMA Network Open. 2022 Aug 1; 5(8):e2225608.
27. Islam R, Imran S,Ashiuzzaman Md, Munim Ali Khan, Md. Detection and Classification of Brain Tumor Based on Multilevel Segmentation with Convolutional Neural Network. J Biomed Sci Eng.2020; 13(4):45-53.
28. Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, Santamaría J, Fadhel MA, Al-Amidie M, Farhan L. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. J. Big Data. 2021;8(1):53.
29. Badjie B, Ülker ED. A Deep Transfer Learning Based Architecture for Brain Tumor Classification Using MR Images. Inf. Technol. Control. 2022; 51(2):332-43.
30. Ge C, Gu IY, Jakola AS, Yang J. Deep semi-supervised learning for brain tumor classification. BMC Med. Imaging. 2020 Jul 29;20(1):87.
31. Srinivasan S, Bai PSM, Mathivanan SK, Muthukumaran V, Babu JC, Vilcekova L. Grade Classification of Tumors from Brain Magnetic Resonance Images Using a Deep Learning Technique. Diagn. (Basel). 2023 Mar 17;13(6):1-20.
32. Irmak E. Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework. IJST-T Eletr Eng. 2021;45(3):1015–36.
33. Stephe S, Jayasankar T, Vinoth Kumar K. Motor Imagery EEG Recognition using Deep Generative Adversarial Network with EMD for BCI Applications.TV-TG. 2022; 29(1):92-100.
34. Alqudah AM, Alquraan H, Abu Qasmieh I, Alqudah A, Al-Shar W. Brain Tumor Classification Using Deep Learning Technique - A Comparison between Cropped, Uncropped, and Segmented Lesion Images with Different Sizes.IJATCSE.2019; 8(6):3684–91.