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Original Article

A Hybrid CNN-SVM Threshold Segmentation Approach for Tumor Detection and Classification of MRI Brain Images

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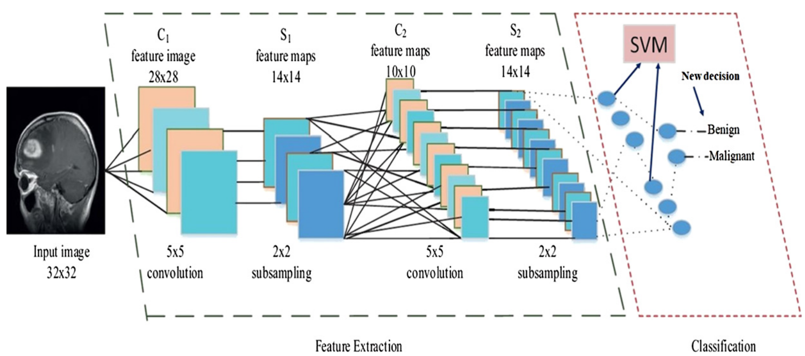
HIGHLIGHTS

- The proposed hybrid model, with consideration of both CNN and SVM model advantages, shows significant improvement.
- A Hybrid method on brain MRI images to detect and classify the tumor has been implemented.
- The overall accuracy of the hybrid CNN-SVM obtained 98.4959%.

GRAPHICAL ABSTRACT



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ABSTRACT

Objective: In this research paper, the brain MRI images are going to classify by considering the excellence of CNN on a public dataset to classify Benign and Malignant tumors.
Materials and Methods: Deep learning (DL) methods due to good performance in the last few years have become more popular for Image classification. Convolution Neural Network (CNN), with several methods, can extract features without using handcrafted models, and eventually, show better accuracy of classification. The proposed hybrid model combined CNN and support vector machine (SVM) in terms of classification and with threshold-based segmentation in terms of detection.
Result: The findings of previous studies are based on different models with their accuracy as Rough Extreme Learning Machine (RELM)-94.233%, Deep CNN (DCNN)-95%, Deep Neural Network (DNN) and Discrete Wavelet Autoencoder (DWA)-96%, k-nearest neighbors (kNN)-96.6%, CNN-97.5%. The overall accuracy of the hybrid CNN-SVM is obtained as 98.4959%.
Conclusion: In today's world, brain cancer is one of the most dangerous diseases with the highest death rate, detection and classification of brain tumors due to abnormal growth of cells, shapes, orientation, and the location is a challengeable task in medical imaging. Magnetic resonance imaging (MRI) is a typical method of medical imaging for brain tumor analysis. Conventional machine learning (ML) techniques categorize brain cancer based on some handicraft property with the radiologist specialist choice. That can lead to failure in the execution and also decrease the effectiveness of an Algorithm. With a brief look

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came to know that the proposed hybrid model provides more effective and improvement techniques for classification.

1. Introduction

The brain is the most significant part that has the most complex structures in the human body [1]. The presentment of the skull layer surrounds the brain makes the difficult study of its behavior and also increases the complexity of the identification of disease [2]. The brain disease is not the same as any other part of the body, but it can be caused by the anomalous growth of cells that ultimately destroys the brain structure and causes brain cancer [3]. However, as per the World Health Organization (WHO) report [4], it is estimated that about 9.6 million around the world died that diagnosed cancer in 2018. As well as around 30% to 50% of those diagnosed with primary cancer. Between many types of cancer, brain cancer is a deadly one. In this manner, the statistics show [5], that around 17,760 adults died that caused brain tumors in 2019. Due to the dire situation and abnormal growth of cancer and the complexity of brain structure, timely diagnosis is necessary. Magnetic resonance imaging (MRI) is widely useful for tumor analysis, with high-quality brain images. In brain imaging, the MRI technique more significant it provides a unique way to have the best fit visualization of maximum both spatial and contrast determination [6].

In the process of an MR image, that's often used to show the different state of disease, as shown in Fig. 1, the (A) shows suspicious inconsistency at the bottom right region. Meanwhile (B, C), shows the Worse state and the tumor takes Wider space. (D) unlike the previous stages, it shows that the tumor is growing and destroying the neighboring cell.

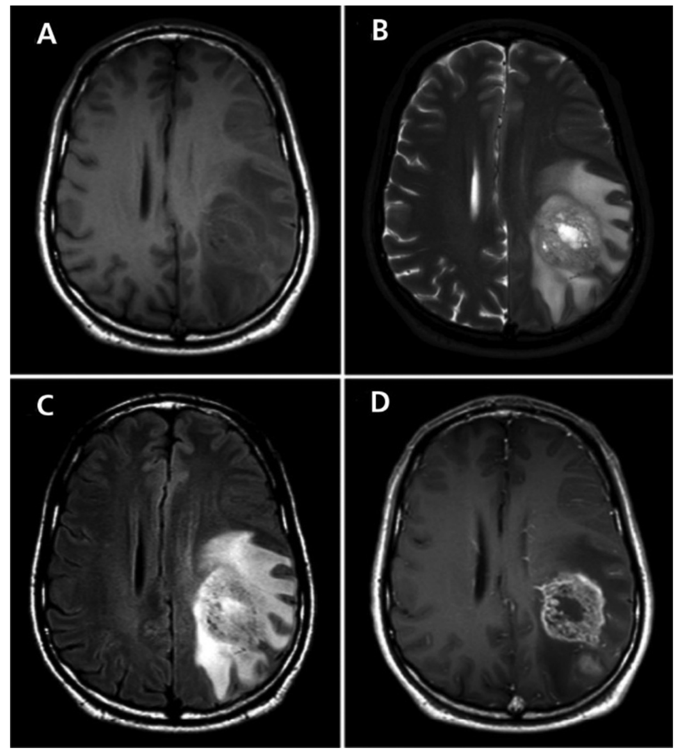

Fig. 1. Growth status of brain tumor from the primary up to the worse state, (A) shows the initial detection with less enhancement, (B, C) shows the acute state of growth of a tumor, and (D) show that taking to destroy the neighbor cells and try spread to another region [40].

Detection of brain tumors [7] is considered as an image segmentation problem to label whether there is a tumor in the image or not. To answer this problem, different ML algorithms and as well as image processing methods are implemented by researchers on MRI images [8]. The main issue in image segmentation is to cluster similar feature vectors of an image. So, accurate extraction of features is the key factor to segment an image [9]. Among the recent studies based on image processing, regain based methods, and thresholding approaches are common [10]. For example, Sherlin and Murugan [11] applied a hybrid model of K-nearest neighbor (KNN) and the Fuzzy C-Mean method, and try with 2D medical images of the brain to define tumor cells and cluster them in the earliest stages from MRI images. In another work, Ashima et al. [12] used combined watershed and neural network (NN) segmentation and also self-organizing maps (SOM), to have segment brain tumors. Abdalla M. et al. [41] proposed a swarm optimization model based on ant lion optimization (ALO), grey wolf optimization (GWO), and artificial bee colony (ABC), it applied these algorithms on Computed tomography (CT) and MRI to segment the liver Disease. The experimental result showed that ALO obtained 94.49%, respectively GWO obtained 94.08, and ABC obtained 93.73% accuracy. In a similar work, Shereen Said et al. [42] proposed a segmentation approach based on the Moth-flame optimization (MFO) technique for the arrangement of abdominal cases of liver MRI images. In the same manner, it uses the Structural Similarity Index (SSI) to find the best fit output & obtained the experimental overall accuracy of 95.66%. As per different studies, while the NN and threshold-based are common for tumor segmentation, it is also possible to have combined with KNN to obtain a better outcome [13]. Brain tumors can be detected using ML methods that required extensive processing. According to a different factor of ML, it mainly needs for human perception and feedback. In the meantime, extensive studies based on ML undertaken to accelerate this process. Prabhjot and Amardeep [14] have used the firefly algorithm to provide a new way to detect the tumor, in the Fireflies method some chemical reaction, that named bioluminescent is happening and produces light in their body which make probable to detect and confine tumor in an accurate way from brain MRI images. In the study that Varuna Shree and Kumar [15] have done, they used discrete wavelet transformation (DWT) with the extraction of gray level co-occurrence matrix (GLCM) features that are based on morphologic processes with probabilistic NN for classification of normal and abnormal tumor images. In another work, Bjoern H. Menze et al. [16] reported the result of a multimodal brain tumor segmentation benchmark that is going to apply on low and high grades of 65 multi-contract MRI patients. Meanwhile, it uses simulation software and convolution human method to show the difficulty of segmentation, and the score range is between (74% - 85%). And the result shows that algorithms based on regions and reaching that point, different methods can take place in top rate.

DL is a NN-based architecture [17], in another viewpoint, it is one of the ML techniques that makes it possible to add many hidden layers among input and output layers [18]. It can be applied in different domains such as speech identification [19], object recognition [20,21], image classification [22]. The DL architecture widely can be used with CNN [23], that easily we can manage the input layers, hidden layers, and output layers [24]. However, the typical

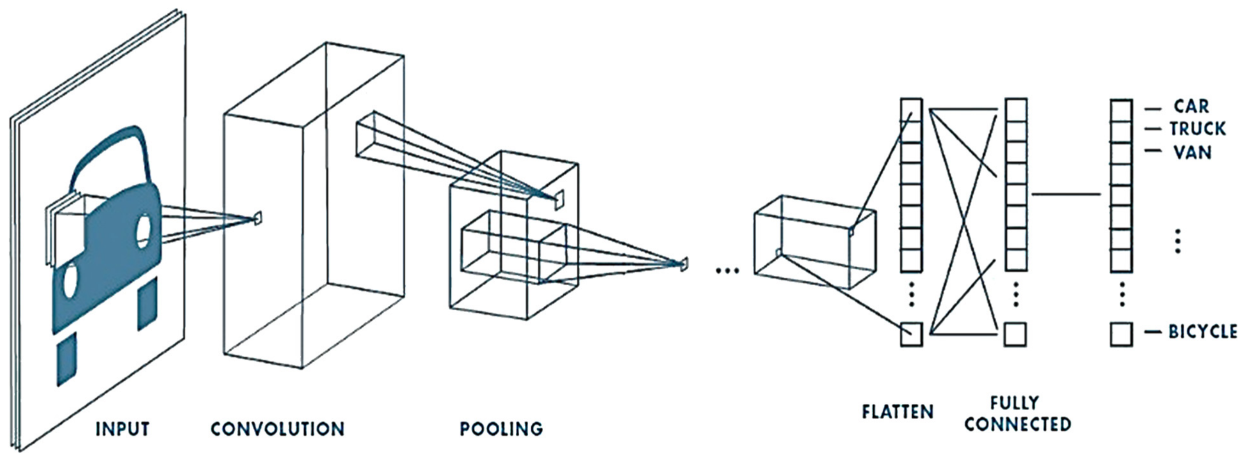

Fig. 2. CNN general architecture of image analysis.

CNN method can define whether an image has an object but without mentioning the location [25].

DL is a flexible and highly efficient technique to solve the problems in medical imaging analysis, including lung cancer, breast cancer, and brain cancer detection [26]. With DL techniques, automatic segmentation can be done effectively on a large amount of MRI datasets [27]. Particularly, the CNN algorithm for an automatic brain MRI image segmentation has produced effective results by considering several features [28]. As per recent studies and solutions that provided to this problem, Hossam, et al. [29], proposed a multi-classification of brain tumor MRI images based on DNN, it tries with two Publicly available datasets to make a new model, that firstly define the tumor type, and in the second step define the glioma grades of detect image. In another study on brain tumor identification, Abdu Gumael, et al. [30] a hybrid technique regularized extreme learning machine (RELM) used to develop an effective brain tumor classifier model. The experimental output of the proposed work shows 94.233% overall accuracy.

Son et al. [34] focus on the latest advancement overlooks into regarding ML for big data systematic & various strategies in terms of present-day figuring conditions for various cultural applications. Chatterjee [35] attempted to provide a significant conception amongst the IoT in BD strategy nearby its different problems, challenges & tried to provide a possible plan by ML strategy. Jhanzhi et al. [36] a position & wormhole attack location system is proposed by utilizing the ML method. Chatterjee [37] has given a short survey of how ML can be used in Bioinformatics. Jain & Chatterjee [38] gives a kind of summary of present & rising ML standards for healthcare informatics & mirrors the assorted variety, intricacy & the profundity & expansiveness of this multi-disciplinary region.

It is debatable that we have gone through many challenges in the process of analyzing and examining brain tumors. The author in the early stages that are the basement of research did not have access to high-quality images to analyze and diagnose brain tumors, this research issue had a problem, which in many cases disrupted the author's thoughts, but with the evaluation and provision of the regular database, this problem was solved. In another step, in order to achieve a unique model and propose a new model, the author uses existing research to examine the best models and design the format of this research, which itself has taken a lot of time in the research structure, and it's rememberable to write that adapting a model and putting it together, it has been one of the challenges in the research process, that has successfully overcome this challenge. The author after so many reviews also found that the proposed method could be used in other areas by providing detailed information and improvement on the concern topic.

In this work, MRI brain images are studied using a threshold-based segmentation method to detect the tumor regain in the image. Also, the detected image with the tumor is going to be classified using hybrid CNN and SVM into one of the considered types: Benign and Malignant. The hybrid CNN-SVM method combined the advantages of both CNN and SVM, which are the most effective and popular methods for image classification. The performance of work evaluated by parameters such as Positive Predictive Value (PPV), False Predictive Value (FPV), and accuracy. The implementation and coding part are done with Python programming language (Version 3.7.6) and also for this propose the OpenCV library, TensorFlow library, and Tkinter for making a proper GUI has been used. The main contribution in this research are as follows:

- The hybrid proposed model combined CNN and SVM in terms of classification and with threshold-based segmentation in terms of detection.
- The overall accuracy of the hybrid CNN-SVM obtained 98.4959%.
- The proposed hybrid model with consideration of both CNN and SVM model advantages shows significant improvement.
- A Hybrid method, on brain MRI images, to detect and classify the tumor has been implemented using the BRATS database in this research study.

The rest of the article is structured as follows: the proposed hybrid method of CNN & SVM is elaborated in section 2. Section 3 described the methodology of the proposed work. Section 4 elaborated on the utilized dataset. Besides, the experimental results and comparison are mentioned in section 5. Conclusion of the present work is discussed in sections 6.

2. Proposed hybrid method of CNN and SVM

The proposed hybrid (CNN-SVM) model is designed to combine both CNN & SVM advantages, as presented in Fig. 2, the general architecture of CNN with layers (Convolution layer, Pooling Layer, flatten layer, and Fully connected layer) are demonstrated [31]. The hybrid model of CNN-SVM will be discussed at the end of this section.

2.1. Convolutional neural network (CNN)

CNN is a typical type of artificial neural network (ANN). In general, this type of network consists of the input layer, hidden layer & output layer [1,6,23,24]. Typically, in this type of network, the output of one layer is used as an input for the next layer. As shown

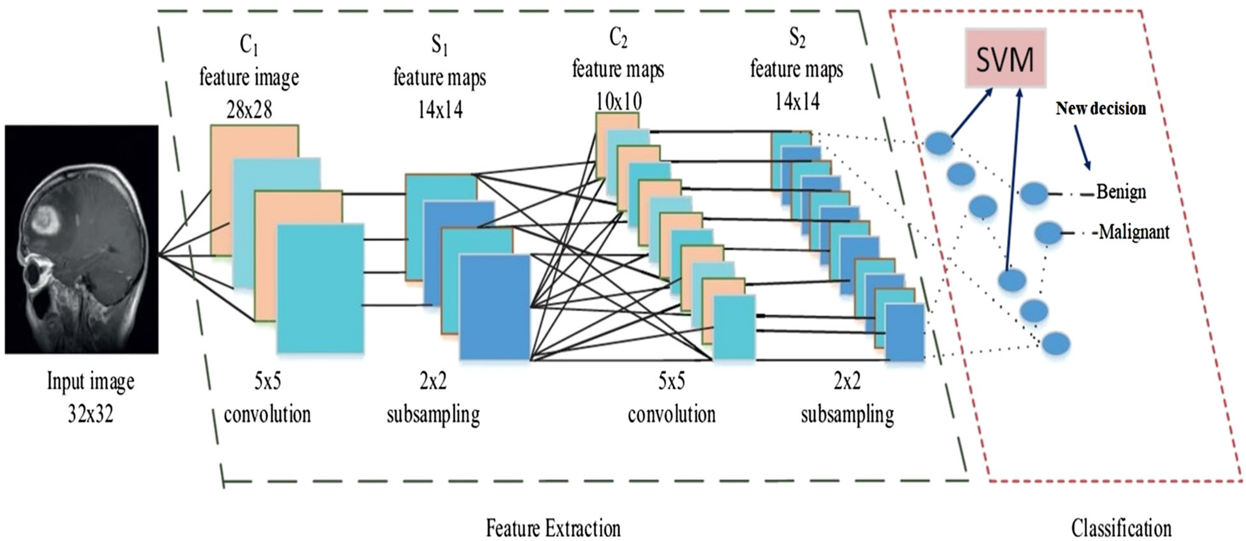

Fig. 3. The structure of hybrid CNN & SVM.

in Fig. 2 the CNN model is used for image analysis that consists of four stages: convolution layer, Pooling layer, Flatten layer, and Fully connected layer, however with a sample look with other architectures you can come to know that the number of layers, as well as type of layers, would be different [23,24].

Basically, in the CNN model, the convolution layer is the first layer to extract the feature from an image; within this, the property of each pixel and relation of neighbor pixels is going to extract with some mathematical operation. After extracting features, the pooling layer going to consider the most significant information by avoiding useless data, this processing called subsampling and tries to reduce the size of the data map without losing importing data and it can be (Max pooling, Avg pooling, Sum Pooling), when the pooling layer applied and the all-important feature is mapped, sometimes the feature mapping makes overfitting, the flatten layer 2D arrays to 1D arrays before applying a fully connected layer. Typically, fully connected is the last layer of a network, and all network have proper connection, the output of fully connected is the final output [32].

2.2. Support vector machine (SVM)

It is a supervised ML that includes the linear and non-linear data and could be utilized for both classification or regression problems. Within this research, the SVM classifier is used in the last layer of the fully connected layer of CNN to improve the flexibility and effectively to fit the date length to turn the kernel [33].

2.3. Hybrid CNN-SVM model

The structure of the combined CNN-SVM model is going to design by replacing the last layer of CNN with the SVM model; therefore, the output of the fully connected layer of CNN is going to process as an input for SVM to make better improvement on the classification. The main reason for combining the advantages of CNN and SVM is that the CNN model with rapid access to add hidden layers that have led to the process of extracting features, as well as increasing accuracy and performance, has always been of paramount importance. However, SVM also, with its unique characteristics in extracting features, has high efficiency and speed among other algorithms. Having this combination can give us access to the best results in brain tumor extraction with MRI images. Fig. 3 demonstrates the structure of the hybrid model of CNN and SVM. In this manner, the CNN model applies different convolution and subsampling and simultaneously convolution layer on basis of 28×28 feature map with having 5×5 convolution, and in the same way feature map 14×14 with having 2×2 convolution. That by applying this function aims to speed up the extraction of information based on the train and test process. After this, the SVM model takes the output of a fully connected layer as input and respectively trains the feature vectors, the classification, and decision making in the better way.

In this case, in addition to the fact that the use of diagnostic knowledge can help reduce mortality from brain tumors, this is a big step in terms of scientific progress and can accelerate the diagnosis of tumors in the very early stages. The author believes that the proposed model enables it by using the principles of precise layering and adjusting filters in images and finally displaying the tumor in the image. On the other hand, the author has found that combining models significantly in the process of influence and results are much more effective than using a single model alone.

3. Methodology

Fig. 4 presents the methodology of the proposed hybrid CNN and SVM model and its stages. The architecture of the hybrid model concluded in five general steps:

I. Input the MRI Image
The MRI image of a brain is taken to segment the tumor region, within this step the image going to take from a specific directory to load on the GUI platform and pass to the next part of the system.

II. Pre-Processing on MRI Brain Image
In this step, the primary functions going to implement on the MRI images to make sure that the system can read the proper input, and make a better condition for image analysis, the steps are as follows:

- **i. Resize the Image:** With consideration of input image the size of each image is different in high and width, in this stage going to define a fixed size like (32×32), to study the whole dataset in the same condition.
- **ii. Remove the Skull:** Due to the significant importance of the brain, within this step, the skull around the brain with some functions is used to remove the background and extract the skull of the brain.
- **iii. Image Filtration:** At this stage, the median filter is applied to remove the noise, which can make a better possibility to

Fig. 4. Different state of Brain MRI image, using threshold segmentation. **(a)** Original image **(b)** Test level 1 of threshold **(c)** Test level 2 of threshold that detect the object on the image.

detect features and also for training and testing conditions it's useful on MRI images.

III. Feature Extraction

Feature extraction is one of the important factors that can affect the result. According to this study, the researchers used different algorithms to find out the feature from the images. Nabil Neggaz et al. [43] implement the Henry gases solubility optimization (HGSO) algorithm to select the feature on 12 different datasets. The main point of this model that makes possible to evaluate the different block size of image feature to find the best factor to find a similar region to the query image. Meanwhile, in another work, Essam et al. [44] used the Harris hawks Optimization (HHO) and also in the same manner for better comparison it uses KNN and SVM in the feature classification process and feature evaluation, and fortunately, this comparison shows good improvement. And in another study Abdel-Azim et al. [45] proposed a novel method based on binary optimization techniques that try by considering the hyperbolic angle of fitness equation in an image to find the best feature in an efficient manner.

Therefore, with consideration of proposed methodology, as shown in Fig. 3, and Fig. 5, the CNN model in the first stage, by having different Convolution layer and pooling layer that is prepared with a different set of filter size is made possible to extract the features of the input image at the moment of the query. And also as illustrates in Fig. 3, the CNN model consists of four convolution layer that by implementing with different filter size, and subsequently used the SVM model in the last layer of CNN and try to select the best fit data to improve the accuracy of the proposed model, and eventually the proposed model obtain great improvement in comparison of existing work.

IV. Image Segmentation

With consideration of the importance of image segmentation, and also its critical phase on the extraction of objects in the field of image processing, pattern recognition. Basically, it partitions the input image into the multiple segments that make it easier to find the best fit data to detect and extract the needed area. The present research study uses the threshold-based segmentation model, by experimenting with the input image in different thresholds and Max value we can enhance the meaningful information. In the main point, the threshold-based segmentation in the first phase divides the grayscale image into two black and white blocks. As you see in Fig. 4, having different threshold levels achieved the best result in brain MRI images.

V. Classification of Brain MRI Images

The images after proper feature extraction and segmentation need to classify, based on this step, firstly, the model is going to train with SVM and CNN, respectively, going to test them with SVM, CNN, and also Hybrid SVM + CNN, with PPV, FPV, Accuracy parameter. And in the last stage going to make a comparative analysis to show the result based on the parameter that is defined to evaluate the performance of the work.

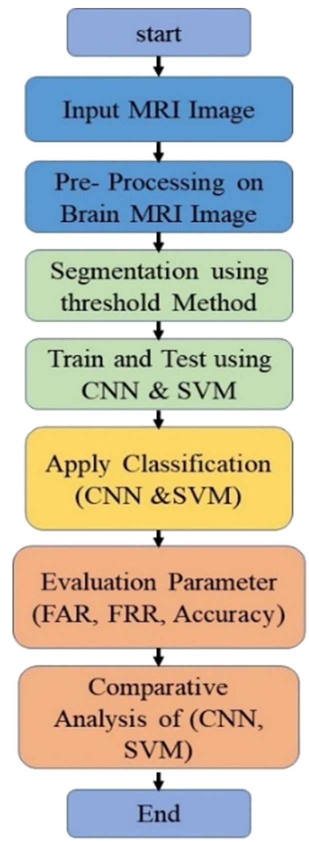

Fig. 5. Proposed Methodology of Hybrid CNN-SVM.

4. Explanation of statistical functions

With a deep understanding of the mathematical function role to find the effective date of an image, within this research, by using different statistical functions tried to detect the best features in brain MRI Images. The brief information with going to describe as below.

A. Mean value: The mean provides the consistency brightness of an image. It has a high quantity of bright pixels. In this manner, the mean defined the sum of all pixels and divided them into the total amount of pixels. The preprocessing step within this function detects the best fit value of an image for the next process.

$$M = \left(\frac{1}{mxn}\right) \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y)$$

In the following equation 'M' stands for the Mean value, in which the (mxn) shows the maximum number of pixels can be valuable in an image, the $(m-1)$ it in every step decrease one point and the x-axis $(x=0)$ starts from the zero points. The $(n-1)$ shows that in every block of grayscale it decreases one point and uses that to make made a link to other blocks. The y-axis $(y=0)$ starts from zero points as the same as the x-axis. And Finally, to have the power for all the point that doesn't miss any point, we try to reach by "$F(x, y)$" to access every point on an image.

B. Variance: It is another factor of an image, that specifies the rate of allocation in gray levels. In a case, if there is a variation on the gray level amount based on mean, then the variance increased too. The variance value provides the measure of each pixel from the mean amount. And, it also provides the average of the square based on the single-pixel and mean value.

$$Variance = \left(\frac{1}{mxn}\right) \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (f(x, y) - M)^2$$

In the same manner the variance equation in addition to the mean value it tries to evaluate to find the difference between the gray level based on the average amount of mean using $(f(x, y) - M)^2$.

C. Standard Deviation: An essential factor that tries to define the difference between the mean data values. And in another viewpoint, it can define the general square of variance, as shown below:

$$SD(\sigma) = \sqrt{\left(\frac{1}{mxn}\right) \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (f(x, y) - M)^2}$$

In SD (α), the main point to show the difference between the processed image data value and the first data value that are available within the image for the first time, based on this it can easily find the changes that are can affect by some filters.

D. Entropy: It used to evaluate the heterogeneity of MRI images or in the place that we try to meet the tumor. We must add this also that entropy is a statistical factor that uses to specify the texture data on the image.

$$Entropy = -\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y) \log_2 f(x, y)$$

Besides of importance the entropy equation, by using $(\log 2 f(x, y))$ it tries to fit the statistical result on the best way and find the exact texture data on the image.

E. Energy: Energy plays the major rule to find the similarity on each pixel of the image. Besides this, the gray level is the essential part, and more importantly, it provides the sum of **(f)** square of gray pixel data on an image.

$$Energy = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f^2(x, y)$$

According to the details that are described the Energy, by using of (F) square (x, f), it tries to double-check every pixel to find the best similar data on each image to show the best result.

Table 1
Comparison of statistical functions based on Benign and Malignant.

Sl. No.	Feature	Range for Malignant (Min)	Range for Malignant (Max)	Range for Benign (Min)	Range for Benign (Max)
1	Mean	73.1	100.2	45.06	54.58
2	Variance	74.09	114.46	78.52	93.22
3	Standard Deviation	8.6	10.69	8.86	9.65
4	Energy	0.19	0.14	0.21	0.38
5	Entropy	7.3	7.5	5.87	6.66
6	Homogeneity	0.94	0.88	0.47	0.9
7	Contrast	0.11	0.46	0.44	0.47
8	Correlation	0.98	0.94	0.89	0.93

F. Homogeneity: It provides a degree value that evaluates the closest origin based on the one GCLM model of an image to another GCLM model of another image.

$$Homogeneity = \sum_{x,y} \frac{p(x, y)}{1 + |x - y|}$$

With consideration of the matrix in every image, it necessary to first evaluate the number of each matrix by using summation x-axis and y-axis (x, y), within this for better output it needs to find all point by $(P(x, y))$ and respectively and one step goes ahead and also decrease that from the whole amount of x and y that is $(1 + (x - y))$.

G. Correlation: it shows how any pixel has correlated to another pixel in an image.

$$Correlation = \frac{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (x, y) f(x, y) - MxMy}{\sigma x \sigma y}$$

Another most significant factor that can help to find the best possible correlation between each pixel is the Correlation factor. In equation $f(x, y)$ make way to access all x-axis and y-axis, and besides, it going to discard the average value of x and y based on the Mean factor to the find the exact relation with other pixels. In the last stage, the lower sigma is used to measure both x and y and find the standard value to remove the error.

H. Contrast: It shows the amount of changes that can affect the way to measure the intensity value among whole image pixels and neighbor pixels. If there is a major change in the gray level, then it shows a high degree of dissimilarity.

$$Contrast = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (x, y)^2 f(x, y)$$

In which the $((x, y)^2 f(x, y))$ shows that x and y both are by considering of x-axis and y-axis to reach the maximum amount that makes this possible to measure the intensity value among whole image pixels and neighbor pixels.

With considering the statistical functions, this study observes the date that helps to find the best result as per the proposed hybrid model it shows the benign and malignant min and max based on different evaluated factors, the obtained information is shown in Table 1.

5. Dataset

The dataset used in this research was taken from BRATS 2015 [39], within this, the BRATS are available in a different version, that comes to solve medical imaging challenge. The BRATS 2015 imaging dataset obtained from BRATS 2012 and BRATS 2013, which can

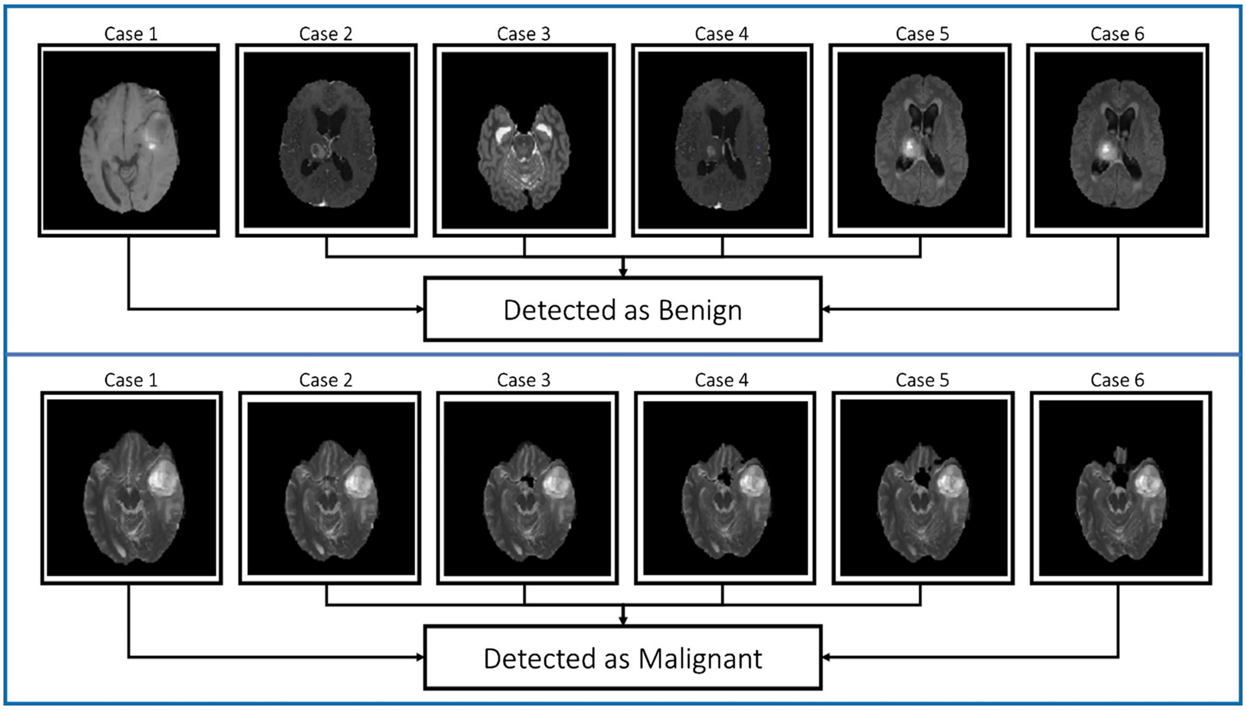

Fig. 6. Illustration of Benign and Malignant Brain Image.

show an updated version of new cases with better performance. It consists of two type training with (110 cases) and respectively testing with (220 cases).

6. Experimental results and discussion

The proposed model evaluates the performance of work on a public image database of BRATS 2015 and implements on Dell laptop with (Core i7 CPU, 8 GB Ram, and 4 GB Nvidia GPU). In the included database, two types of tumors that are benign and malignant with low and high grades are available. As per the proposed methodology, after preprocessing, the extracted feature with consideration of training and testing is going to process and set in specific tests and train category as shown in Fig. 3. In this process, as shown in Fig. 3 and Fig. 5, the CNN model, extract the features and with various steps transfer to fully connected layer using the activation function. The extracted image features going to train the CNN classifier. On the other hand, the SVM model takes the fully connected output of CNN as an input to the process and train each image. At the last stage, the classifier is going to categorize whether the input image is malignant or benign, as shown in Fig. 6. Eventually, the accuracy of the hybrid proposed CNN-SVM is evaluated by considering the evaluation defined parameter.

6.1. Evaluation parameters

(a) Accuracy: Based on image classification, the accuracy is a percentage that shows the total amount of properly classification of pixels to the number of pixels in the image. It evaluates the complete properly pixels in an image.

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

(b) PPV: In addition to accuracy, the true positive (TP) show the probability of pixels that correctly classified.

$$\text{Positive Predictive Value} = \frac{\text{TP}}{(\text{TP} + \text{FP})}$$

Table 2
Comparison of existing models with proposed Hybrid CNN and SVM.

The existing model along with the method and obtained accuracy			
Existing works	Method		Accuracy
[31]	Regularized Extreme Learning Machine (RELM)		94.233%
[24]	Deep Convolutional Neural Network (DCNN)		95%
[20]	Deep neural networks (DNN), deep wavelet autoencoder (DWA)		96%
[40]	K-Means, K-nearest neighbor (KNN)		96.6
[23]	Convolutional Neural Networks (CNN)		97.5%
Proposed hybrid model classification accuracy			
Stage	SVM	CNN	Hybrid
Benign	61.67%	97.724%	98.5873%
Malignant	67.98%	97.8455%	98.6702%

(c) FPV: However, with underusing accuracy and TP, in image analysis, true negative (TN) is the probability pixel identification that logically shows normal but classified as an abnormal feature.

$$\text{False Predictive Value} = \frac{\text{FP}}{(\text{FP} + \text{TP})}$$

6.2. Result analysis

The proposed technique got better outcomes compared with existing models. In Table 2, as shown the accuracy of existing techniques compared with the proposed model. Meanwhile, the accuracy of hybrid CNN-SVM in overall comes 98.495%, in another view for classification based on Benign tumor with SVM got 61.67%, for CNN got 97.724% and respectively on the hybrid model obtained 98.5873%. The classification based on Malignant tumor with SVM got 67.98%, for CNN got 97.8455%, and respectively on the hybrid model obtained 98.6702%.

As shown in Fig. 7, the comparative analysis of the hybrid proposed model shows that by considering the strongest point of both CNN and SVM, can lead us to have improved models with a better

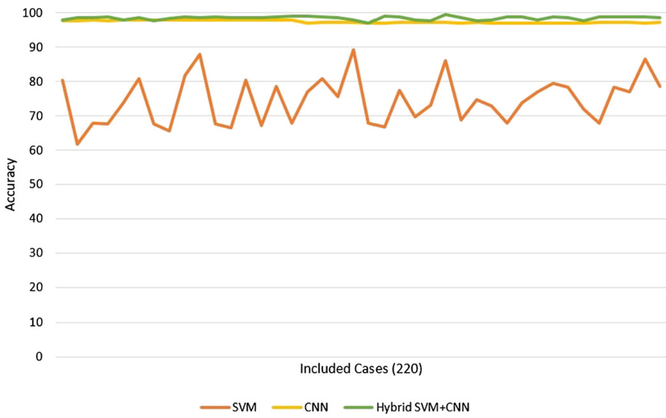

Fig. 7. Comparative analysis of CNN, SVM with Hybrid CNN-SVM model. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

result on classification. As per this study, the overall average accuracy is as flows, SVM with 72.5536%, respectively the CNN with 97.4394%, and the Hybrid model obtained 98.4959%. However, with consideration of other evaluation parameters such as PPV and FPV, we come to know that the classification effects this parameter the same as shown in Fig. 7.

If we take a closer look at the graph presented in Fig. 8, we will see that the accuracy level of CNN and SVM separately does not show good progress, that the complete information mention in Table 2. At the same time, the accuracy degree of proposed hybrid CNN and SVM express significant progress in the same way.

However, FPV is another important feature for evaluating the correct performance of an activity. Fig. 9, shows that CNN and SVM did not show a better result when it used individually, but the proposed method has done this process with higher accuracy.

At the same time, PPV, which shows the degree of correct image classification. In fact, with a close view of CNN and SVM, we come to know that the result is not satisfactory and needs more improvement. Which the proposed model has taken the fruitful step, which is shown in Fig. 10, and it improved with a better rate.

Along with the proposed method with a defined evaluation parameter, as shown in Fig. 7, 8, 9, 10, besides high accuracy, other features such as FPV and PPV in the hybrid model in comparison of individually CNN and SVM have been much better results. And also, as per the comparison of proposed research work with existing research studies, as shown in Fig. 11, the proposed work shows a high rate, and we can have better classification output.

7. Conclusion

Brain tumor detection and classification due to abnormal growth of cells or portable progression throughout the body, is one of the deathless diseases in the world, among other diseases. A Hybrid method, on brain MRI images to detect and classify the tumor, has been implemented using the BRATS database in this research study. The implemented system tries to classify brain images as a benign and malignant tumor using supervised hybrid CNN and SVM techniques. The primary preprocessing steps have been implemented to normalize the input images, and also significant features extract from the preprocessed image by using the Maximally stable extremal regions (MSER) method and then segmented with threshold-based segmentation technique. The labeled segmented features are pass as input to hybrid CNN and SVM algorithms to classify brain MRI images. The result shows the highest correctly classified with PPV and lowest of FPV, and overall, it achieved 98.4959% classified correctly this the hybrid model, whereas, SVM Separately got 72.5536%, and CNN obtained 97.4394%. With a brief look came to know that the proposed hybrid model provides more effective and improvement techniques for classification. In future studies, for better decision making, the faster CNN with SVM and other optimization methods (bio-inspired algorithms) can be used to show the overall improvement. And due to the detection of the tumor, consideration of size and exact location of the tumor also in the case.

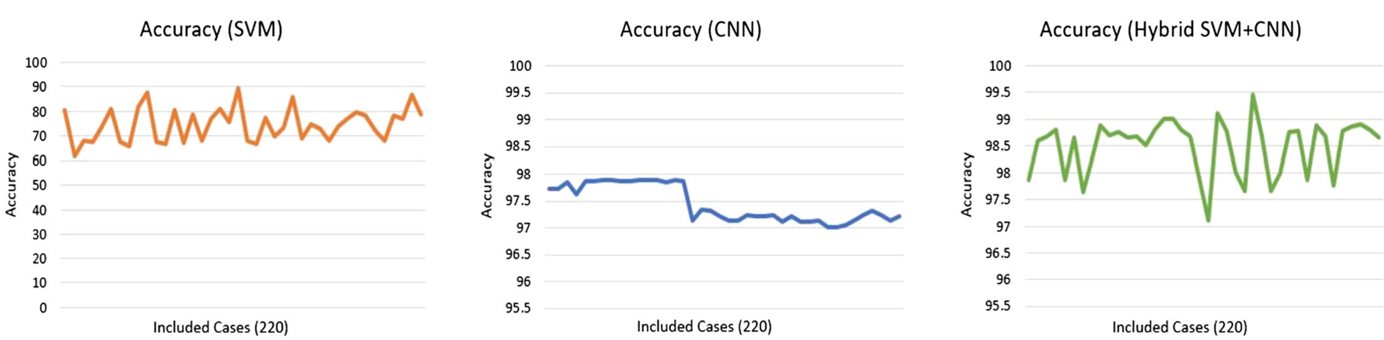

Fig. 8. Accuracy comparison of CNN, SVM with Hybrid CNN-SVM model.

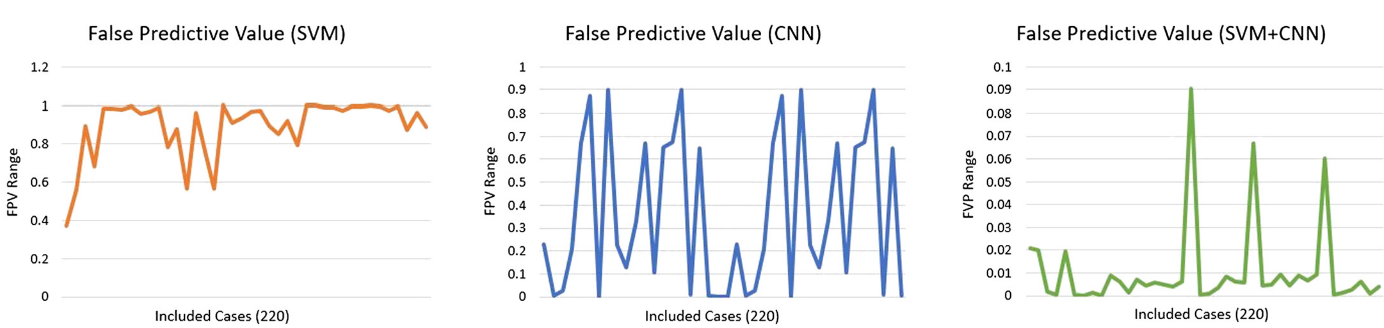

Fig. 9. FPV comparison on CNN, SVM with Hybrid CNN-SVM model.

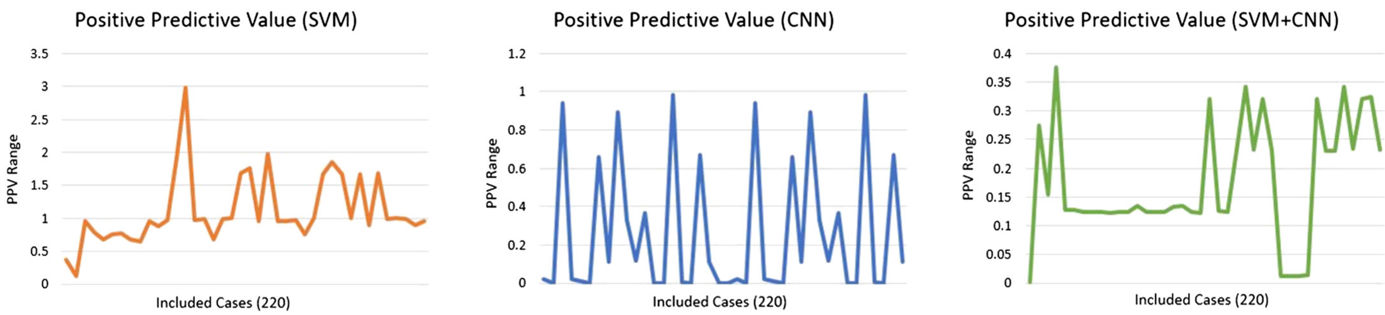

Fig. 10. PPV comparison on CNN, SVM with Hybrid CNN-SVM model.

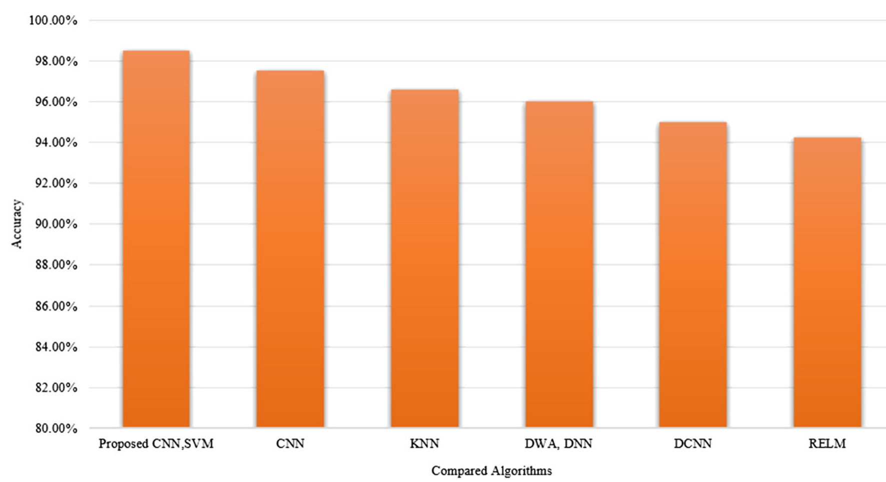

Fig. 11. Comparison of Proposed work with the existing model.

Human and animal rights

The authors declare that the work described has not involved experimentation on humans or animals.

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Author contributions

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship.

Declaration of competing interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

References

[1] Yang A, Yang X, Wu W, Liu H, Zhuansun Y. Research on feature extraction of tumor image based on convolutional neural network. IEEE Access 2019;7:24204–13.
[2] Bandyopadhyay SK. Pre-processing and segmentation of brain image for tumor detection. JIS University, India 2019;1:15–9.
[3] Li Y-Q, Chiu K-S, Liu X-R, Hsiao T-Y, Zhao G, Li S-J, et al. Polarization-sensitive optical coherence tomography for brain tumor characterization. IEEE J Sel Top Quantum Electron 2019;25:1–7.
[4] Shakeel PM, Tobely TEE, Al-Feel H, Manogaran G, Baskar S. Neural network-based brain tumor detection using wireless infrared imaging sensor. IEEE Access 2019;7:5577–88.
[5] Board CE. Cancer.Net. American Society of Clinical Oncology (ASCO), 2019. [Online]. Available: https://www.cancer.net/cancer-types/brain-tumor/statistics. [Accessed 2019].
[6] Akkus Z, Galimzianova A, Hoogi A, Rubin DL, Erickson BJ. Deep learning for brain MRI segmentation: state of the art and future directions. J Digit Imaging 2017;30(4):449–59.
[7] Fabelo H, Ortega S, Szolna A, Bulters D, Piñeiro JF, Kabwama S, et al. In-vivo hyperspectral human brain image database for brain cancer detection. IEEE Access 2019;7:39098–116.
[8] Ahmadvand A, Daliri M. Brain MR image segmentation methods and applications. OMICS J Radiol 2014;3(4):e130.
[9] Popoola JJ, Godson TE, Olasoji YO, Adu MR. Study on capabilities of different segmentation algorithms in detecting and reducing brain tumor size in magnetic resonance imaging for effective telemedicine services. Eur J Eng Res Sci 2019;4:23–9.
[10] Hu K, Gan Q, Zhang Y, Deng S, Xiao F, Huang W, et al. Brain tumor segmentation using multi-cascaded convolutional neural networks and conditional random field. IEEE Access 2019;7:92615–29.
[11] Sherlin DMD. Implementation of hybrid KNN – FCM for brain tumor segmentation. IJEDR 2017;5:1251–4.
[12] Anand A. Brain tumor segmentation using watershed technique and self-organizing maps. Indian J Sci Technol 2017;10.
[13] Arnaud A, Forbes F, Coquery N, Collomb N, Lemasson B, Barbier EL. Fully automatic lesion localization and characterization: application to brain tumors using multiparametric quantitative MRI data. IEEE Trans Med Imaging 2018;37:1678–89.
[14] Kaur P, Kaur A. An automated brain tumor detection in MRI using firefly optimized segmentation. Int J Adv Res Comput Sci Softw Eng 2017;7.
[15] Shree NV, Kumar TNR. Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network. Brain Inform 2018;5:23–30.
[16] Menze BH, Jakab A, Bauer S, Kalpathy-Cramer J, Farahani K, Kirby J, et al. The multimodal brain tumor image segmentation benchmark (BRATS). IEEE Trans Med Imaging 2014;34:1993–2024.
[17] Loganayaki M, Geetha K. Brain tumor identification using multi-atlas segmentation. IJRTE 2019;8.
[18] Sindhia R, Shankar Mahalingam SP. Brain tumor detection using MRI by classification and segmentation. SSRG Int J Med Sci 2019;6:12–4.

[19] Khan MA, Lali IU, Rehman A, Ishaq M, Sharif M, Saba T, et al. Brain tumor detection and classification: a framework of marker-based watershed algorithm and multilevel priority features selection. Microsc Res Tech 2019;82:909–22.
[20] Mallick PK, Ryu SH, Satapathy SK, Mishra S, Nguyen GN, Tiwari P. Brain MRI image classification for cancer detection using deep wavelet autoencoder-based deep neural network. IEEE Access 2019;7:46278–87.
[21] Kaur H, Kaur S. Improved brain tumor detection using object-based segmentation. Int J Eng Trends Technol 2016;13:1–6.
[22] Zhang Y, Dong Z, Wu L, Wang S. A hybrid method for MRI brain image classification. Expert Syst Appl 2011;38(8):10049–53.
[23] Seetha J, Raja SS. Brain tumor classification using convolutional neural networks. Biomed Pharmacol J 2018;11:1457.
[24] Hemanth DJ, Anitha J, Naaji A, Geman O, Popescu DE, et al. A modified deep convolutional neural network for abnormal brain image classification. IEEE Access 2018;7:4275–83.
[25] Gamage PT. Identification of brain tumor using image processing techniques. Faculty of Information Technology, University of Moratuwa. https://www.researchgate.net/publication/276133543, 2017.
[26] Xing F, Xie Y, Yang L. An automatic learning-based framework for robust nucleus segmentation. IEEE Trans Med Imaging 2015;35:550–66.
[27] Dahab DA, Ghoniemy SSA, Selim GM, et al. Automated brain tumor detection and identification using image processing and probabilistic neural network techniques. Int J Image Process Vis Commun 2012;1:1–8.
[28] Baraiya N, Modi H. Comparative study of different methods for brain tumor extraction from MRI images using image processing. Indian J Sci Technol 2016;9:1–5.
[29] Sultan HH, Salem NM, Al-Atabany W. Multi-classification of brain tumor images using deep neural network. IEEE Access 2019.
[30] Gumaei A, Hassan MM, Hassan MR, Alelaiwi A, Fortino G. A hybrid feature extraction method with regularized extreme learning machine for brain tumor classification. IEEE Access 2019;7:36266–73.
[31] Sec S, Mahalakshmi R. An efficient strategy over brain tumour analysis using image processing technique. Int J Pharm Technol 2017;9:30687–96.
[32] Demirhan A, Törü M, Güler I. Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks. IEEE J Biomed Health Inform 2014;19:1451–8.
[33] Alkhaleefah M, Wu Chao-Cheng. A hybrid CNN and RBF-based SVM approach for breast cancer classification in mammograms. In: 2018 IEEE international conference on systems, man, and cybernetics (SMC). IEEE; 2018.
[34] Tripathy HK, Acharya BR, Kumar R, Chatterjee JM. Machine learning on big data: a developmental approach on societal applications. In: Big data processing using spark in cloud. Singapore: Springer; 2019. p. 143–65.
[35] Chatterjee J. IoT with big data framework using machine learning approach. Int J Mach Learn Networked Collab Eng 2018;2(02):75–85.
[36] Jhanjhi NZ, Brohi SN, Malik NA. Proposing a rank and wormhole attack detection framework using machine learning. In: 2019 13th international conference on mathematics, actuarial science, computer science and statistics (MACS). IEEE; 2019. p. 1–9.
[37] Chatterjee JM. Bioinformatics using machine learning. Glob J Internet Interv IT Fusion 2018;1(1) (online).
[38] Jain V, Chatterjee JM. Machine learning with health care perspective; 2020.
[39] https://www.smir.ch/BraTS/Start2015#!#download.
[40] Anitha V, Murugavalli S. Brain tumour classification using two-tier classifier with adaptive segmentation technique. IET Comput Vis 2016;10(1):9–17.
[41] Mostafa A, Houssein EH, Houseni M, Hassanien AE, Hefny H. Evaluating swarm optimization algorithms for segmentation of liver images. In: Advances in soft computing and machine learning in image processing. Springer; 2018. p. 41–62.
[42] Said S, Mostafa A, Houssein EH, Hassanien AE, Hefny H. Moth-flame optimization-based segmentation for MRI liver images. In: International conference on advanced intelligent systems and informatics; 2017.
[43] Neggaz N, Houssein EH, Hussain K. An efficient Henry gas solubility optimization for feature selection. Expert Syst Appl 2020:113364.
[44] Houssein EH, Hosney ME, Oliva D, Mohamed WM, Hassaballah M. A novel hybrid Harris hawks' optimization and support vector machines for drug design and discovery. Comput Chem Eng 2020;133:106656.
[45] Hussien AG, Houssein EH, Hassanien AE. A binary whale optimization algorithm with hyperbolic tangent fitness function for feature selection. In: 2017 eighth international conference on intelligent computing and information systems (ICICIS); 2017.