Real-time Multi Fractal Ensemble Analysis CNN Model for Optimizing Brain Tumor Classification and Survival Prediction Using SVM

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Classification and Prediction of brain tumors towards survival prediction has been well studied. There exist different schemes around the problem but struggle with poor performance in survival prediction and classification. To overcome the deficiency in classification, a real-time multi-fractal ensemble analysis CNN model (RMFEA-CNN) is presented in this article. The method not just considers basic low-level features like gray, texture, and binary features but also considers Coverage, Mass Index, and Intensity Fraction features. By preprocessing the image with the histogram equalization technique, the image quality has been increased. Further, the above-said features are extracted and trained by generating a multi-fractal ensemble towards various classes using a convolution neural network. The intermediate layers apply a support vector machine toward the classification of an ensemble. The neurons of the intermediate layer apply a support vector machine in estimating Ensemble Centric Coverage Support Measure (ECCSM), Ensemble Centric Mass Support Measure (ECMSM), and Ensemble centric Intensity Support Measure (ECISM) towards various classes. Disease Attraction Weight (DAW), which is measured by the support vector machine using a variety of support metrics, is computed using the estimated values by the method and produced at the output layer. The method carry out disease prediction and estimates survival stage support (SSS) measures to perform survival prediction, as determined by the DAW value. The proposed method improves disease prognostication performance and introduces a lower false ratio.

Keywords: Brain Tumor Classification; CNN; Medical Imaging; Survival Prediction; SVM; RMFEA-CNN.

A Brain tumor is the most deadly disease being identified in the medical domain which affects human life to a different extent. Sometimes, the disease would claim the life of the person. However, diagnosing the presence of disease at the earlier stage would increase the span of life. The presence of a tumor in the brain has been diagnosed with the support of a brain image captured in form of an MRI (Multiple Resonance Image). The diagnosis is performed in several ways either with a medical practitioner or with a support system. The result of diagnosis by a medical practitioner has human errors which are not acceptable. So most medical solutions depend on decisive support systems. The decisive support systems are capable of producing accurate results in different medical problems.

Image processing algorithms are greatly used in several medical problems. Also, they have been used in different security problems like face recognition and fingerprint recognition. Similarly, image processing algorithms are used in different medical problems like tumor classification, mammogram classification, and so on. Towards brain tumor classification different machine learning algorithms are used like support vector machine (SVM), K means clustering, principle component analysis (PCA), genetic algorithm, neural network, and so on. However, the performance of brain tumor classification is not up to the expected level. The existing approaches suffer to achieve higher classification accuracy with a higher false ratio.

Decisive support systems are designed for the support of medical practitioners in many situations. By enforcing decisive support systems with brain tumor classification, classification accuracy can be improved. The decisive systems take the input brain image and extract the features from the brain image. According to the features extracted, the system would measure the similarity among various features extracted from different samples. According to the similarity measure, the class of image has been identified. There exist numerous decisive systems available to support brain image classification, however, the accuracy of the algorithm is greatly depending on the feature being used and the similarity measured. The problem of brain tumor classification is performed using various features like gray, texture, shape, and so on. Still, the methods suffer to achieve higher performance in classification.

By adopting a support vector machine with a convolution neural network, the neurons could be designed to compute support values on various features towards various disease classes of brain tumors. By considering this, and handling the inaccuracy issues of existing schemes, a novel multi-fractal ensemble analysis CNN model (RMFEA-CNN) is presented in this section. However, there exist different approaches in brain tumor classification, the CNN has the beauty of convolving the features of the brain images and supports the classification to be performed in a short period with higher accuracy. By adapting CNN with the model, the high dimensional data can be handled easily with less time and higher accuracy. Also, the method enforces classification with CNN and optimizes the classification problem with a support vector machine algorithm. The proposed RMFEA-CNN model has been designed to generate several ensembles and for each of them, the method would compute the value of different ensemble support values. According to different ensemble support values, the method would compute attraction weight. Based on the disease attraction weight, the classification would be performed.

The proposed model has been optimized with the genetic algorithm which generates various ensembles to which the CNN model would compute support values using the support vector machine algorithm. Based on the support values, the value of disease attraction weight is measured towards classification. The detailed approach is discussed in the next sections.

Related Works

The methods of brain tumor classification are described by various researchers in the literature. This section points out some of the most efficient approaches which are described in the recent trend.

In[1], the author performs a comparative analysis of various CNN transfer learning models in classifying brain images. An automatic tumor segmentation model is presented for the classification of brain images in[2], which uses the local independent projection-based classification (LIPC) method in classifying voxels into various classes. A regularized extreme learning machine (RELM) based feature extraction scheme is presented in[3], for efficient classification of brain images. The method performs normalization with a min-max algorithm tumor classification approach. A multi-level feature extraction scheme is presented in[4], for effective classification which extracts features using a pre-trained Inception-v3 model and concatenated these features for brain tumor classification. A transfer learning-based approach is presented towards brain image classification in[5], which extracts features using pre-trained CNN and is classified using softmax, Support Vector Machine (SVM), and K-Nearest Neighbor (K-NN). A random forest and active contour model-based approach are presented in[6], which segments the images using the random forest to extract structural information where the active contour model is used towards classification. In[7], a data augmentation model with a pairwise Generative Adversarial Network (GAN) is presented which combines slice-level glioma subtype classification results by majority voting. A deep learning model is presented for classification in[8], which uses CNN towards classifying meningioma, glioma, and pituitary tumors. A convolutional neural network based on complex networks (CNNBCN) is presented in[9], which uses randomly generated graph algorithms in generating the network structure. A transfer learning-based classification scheme is presented in[10], which uses popular deep learning architectures to develop a brain tumor diagnostic system.

Towards classifying brain tumors a cumulative variance method (CVM) is presented in[11], which uses the CVM in feature extraction to support the classification with KNN and other approaches. A hybrid machine learning approach for brain image classification is presented in[12], which uses texture, shape, and intensity features in clustering samples. According to the samples clustered, the random forest classifier is used for classification. A multi-view dynamic fusion framework is presented in[13], The multi-view deep neural network architecture is used in integrating different segmentation results to improve performance. A representation-based radiomics (SRR) is presented in[14], which extracts the features using a dictionary-based approach and multi-feature collaborative sparse representation classification is used. A Bayesian CapsNet framework is presented in[15], which handles the uncertainty in classification. An automated segmentation model is presented in[16], for brain image classification, which uses a learning-based approach, and Bat Algorithm with Fuzzy C-Ordered Means (BAFCOM) has recommended segmenting the tumor. A brain tumor segmentation algorithm with missing modalities is presented in[17], where the correlation model transforms all the individual representations to the latent multi-source correlation representations to perform efficient classification.

A mutual information-accelerated singular value decomposition (MI-ASVD) model is presented in[18], which generates grey-level

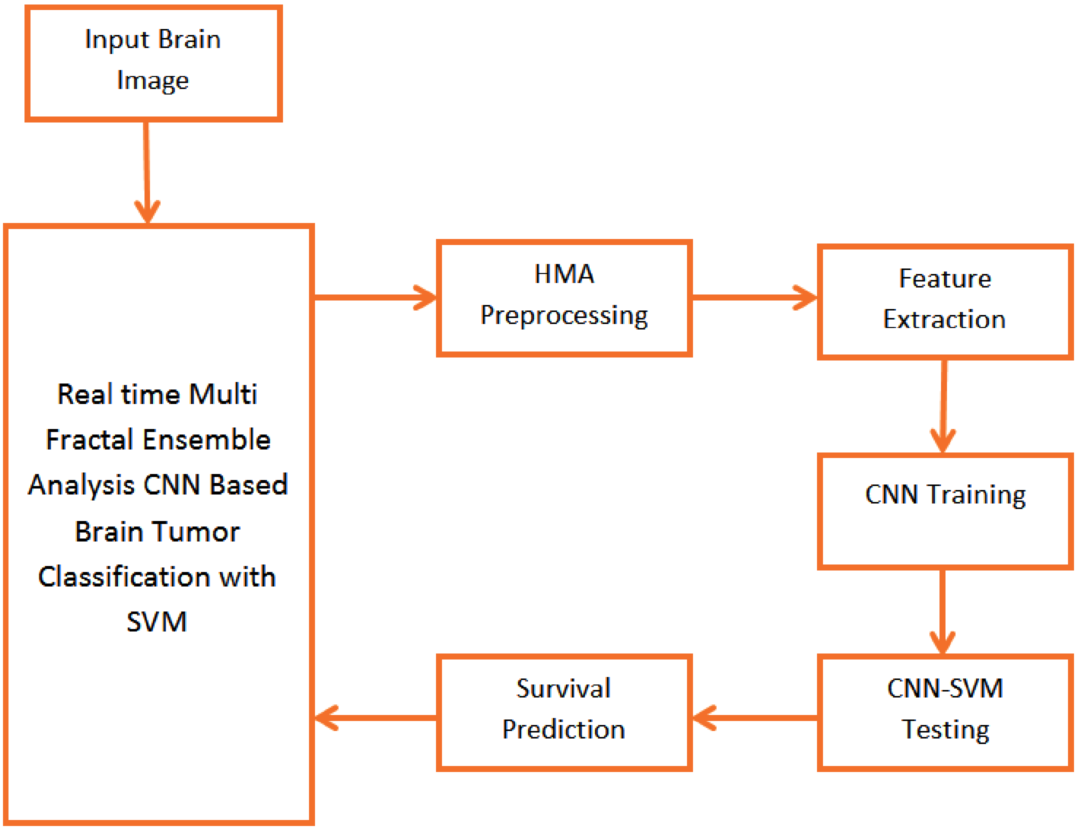

Fig. 1. Architecture of Proposed RMFEA-CNN Approach

run-length matrix (GLRLM), texture, and color intensity features towards classification with a neural network. A Gaussian Convolutional Neural Network (GCNN) based approach is presented in[19], which handles different grades of tumors. A Fully Automatic Heterogeneous Segmentation using a Support Vector Machine (FAHS-SVM) has been proposed in[20], which uses structural, morphological, and relaxometry details in classification. Edge-enhanced dominant valley and discrete Tchebichef (EDV-DT) approach to segment images into several partitions with more accuracy and speed is proposed in[21]. Discrete Tchebichef moment feature extraction is used for the segmented images to decrease the dimensionality of the segmented texture image. This helps to increase the rate of feature extraction in turn. Multi-Feature Frequency Similarity Multi-Layer Perceptron Neural Network (MFFS-MLPNN) is proposed in[22]. MRI brain image is preprocessed by contrast curvature-based iterative shearlet filter and the image is enhanced by using the histogram equalization technique. By using the cross-multilinear local embedding method the tumors are extracted.

All the above-discussed approaches suffer to achieve higher performance in brain image classification.

Real-time Multi Fractal Ensemble Analysis CNN-Based Brain Tumor Classification with SVM

The proposed RMFEA-CNN model maintains the classified brain images. From the images, the method applies the histogram equalization technique which enhances the quality of the image initially. With the preprocessed image, the method extracts different features like gray, texture, binary features, Coverage, Mass Index, and Intensity Fraction features. Once the features are extracted, the method generates an ensemble and trains the convolution neural network with the features extracted. The CNN is designed with four layers and the first one is the input layer which takes the features extracted. The output layer returns different support values on various factors. At the test phase, the neurons at the intermediate layer neurons apply a support vector machine to compute the value of Ensemble Centric Coverage Support Measure (ECCSM), Ensemble Centric Mass Support Measure (ECMSM), and Ensemble centric Intensity Support Measure (ECISM) towards various classes. This has been iterated by generating different ensembles on the feature vector given. For each of them, the method would compute the above-mentioned ECCSM, ECMSM, and ECISM values. Based on these values the method computes the value of DAW to perform classification. Similarly, for survival prediction, the method computes the value of Survival Stage Support based on the values of Ensemble Centric Coverage Support Measure (ECCSM) and Ensemble Centric Mass Support Measure (ECMSM) (SSS). According to the value of SSS, the method classifies the survival class and performs survival prediction. This section details the approach and functionalities in detail.

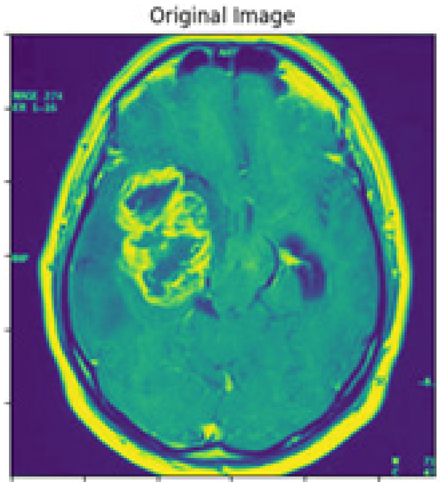

Fig. 2. Input Image

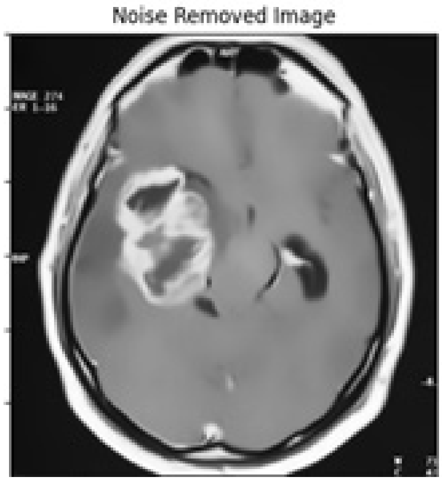

Fig. 3. Result of HMA Preprocessing

The architecture of the proposed RMFEA-CNN-based brain image classification with a genetic algorithm has been presented in Figure 1, where each functional stage has been discussed in detail in this section.

HMA (Histogram Mean Approximation) Preprocessing

The input brain image given would contain several noisy features. It is necessary to eliminate such noisy features to support the effective classification of images. To handle this, a gray-level histogram approximation technique is used. The method first generates the gray histogram at the window level. The method splits the image into several blocks, and for each block, a histogram has been generated. According to the gray histogram, the method optimizes the minimum gray value with the least number of pixels. Based on the selected least appearance pixel, the method identifies the noisy pixels and adjusts the pixel with the mean average value measured with the two-hop neighbor gray value. The preprocessed image has been used to perform brain image classification.

Table 1. Details of Evaluation

Constraint	Value
Tool Used	Python
Data set	Brats 2018
Number of Classes	2
Number of Instances	10000

Algorithm

Given: Brain Image B

Obtain: Preprocessed image Pri.

Start

Read B.

Window Image Set Wimgs = $\overset{size(B)}{\underset{i=1}{Split(B, size(window))}}$

For each window image wi

Histogram values H = $\overset{size(Wimgs)}{\underset{i=1}{Histo(Wimgs(i))}}$

Identify least numbered histogram Lhs = $\overset{size(H)}{\underset{i=1}{Least(H(i))}}$&& Min(count(H(i)))

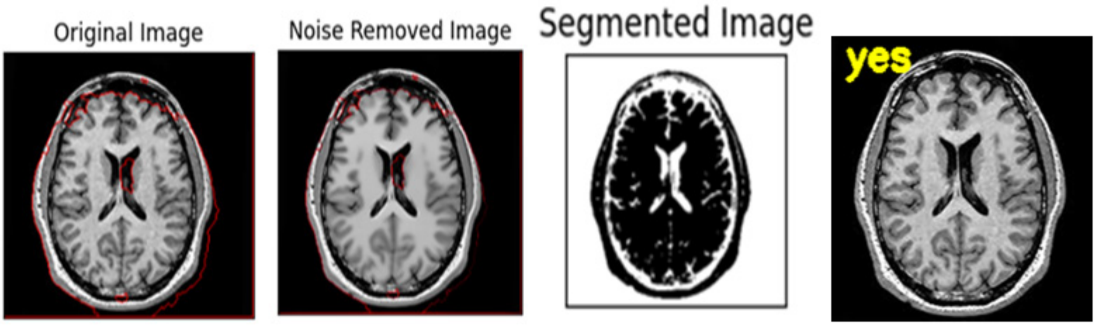

Fig. 4. Results of Brain Tumor Classification (Positive Class)
4(a) Original Image; 4(b) Noise Removed; 4(c) Segmented image ; 4(d) Classified image

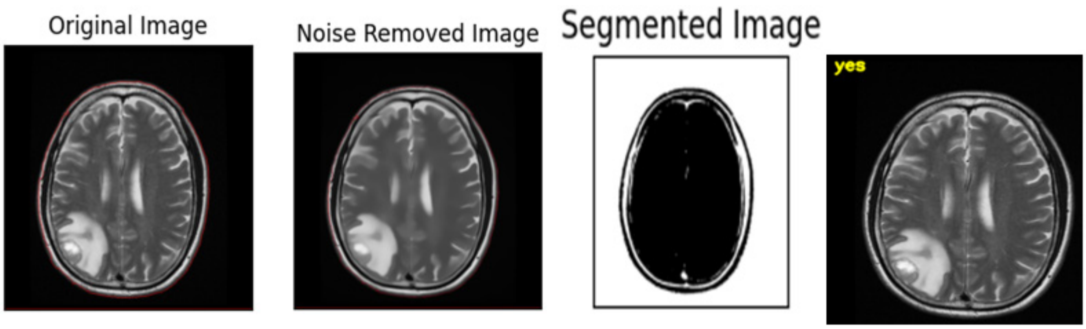

Fig. 5. Result of Brain Tumor Classification (Positive Class)
5(a): Original Image; 5(b): Noise Removed; 5(c): Segmented; 5(d): Classified

Compute two hop mean Thm =
$Mean(\ \sum twohopneighbors(wi(k) == lhs))$
Adjust the noisy pixel.
For each noisy pixel p
Wi(p) = Thm
End
End
Pri = B.
Stop

The preprocessing algorithm generates the window images and for each of them, it generates the gray histogram. According to the histogram value, a set of noisy pixels are identified and each has been adjusted by computing the mean histogram value. The preprocessed image has been used to perform brain image classification.

The original image given for the analysis is given in Figure 2, which has been applied with the HMA algorithm towards quality enhancement. The result of HMA preprocessing is presented in Figure 3, which removes the noise and enhances the quality of the image according to the histogram mean approximation scheme.

Feature Extraction

The preprocessed image has been used in extracting features like gray, texture, and binary to measure Coverage, Mass Index, and Intensity Fraction features. To extract the features first, the method generates the grayscale image and extracts gray, and texture, and extracts binary features by generating the binary image. Using the texture feature extracted, the method measures the coverage value as follows:

$$\text{Coverage Feature (CF)} = \frac{\sum pixels \in T}{\sum pixels \in Image} \times 100 \quad \text{...(1)}$$

Where T is the texture extracted and Image is the input image.

Similarly, the method extracts the mass index value according to the grayscale value. It has been measured as follows:

$$\text{Mass Index (MI)} = \frac{Count(\sum_{i=1}^{size(Gimage)} Gimage(i).vallue > 200)}{size(Gimage)} \quad \text{...(2)}$$

Finally, the intensity fraction is measured according to the grayscale values of the image pixel. It represents the closeness of the image to a specific class of image. It has been measured as follows:

$$\text{Intensity Fraction (IF)} = \frac{Count(\sum_{i=1}^{size(Gimage)} Gimage(i).vallue > 230)}{size(Gimage)} \quad \text{...(3)}$$

Such features extracted are converted into a multi-fractal ensemble to support the classification.

CNN-SVM Training

The proposed approach trains the convolution neural network according to the features extracted. At the input layer, the number of neurons is generated according to the number of samples in the data set. Each neuron has been initialized with the features extracted and the measures computed. At the convolution layer, the neurons convert or reduce the size of features into reduced dimensions. The binary pattern generated has been reduced to a small size and the texture feature has been convolved to a minimum dimension. The convolved features are assigned to different classes of brain tumors like malignant and benign.

CNN-GA Testing

In the testing phase, the input test image has been applied with preprocessing and features like gray and texture are extracted. Also with the gray and texture features, the method generates the local binary pattern LBP and measures the coverage feature, mass index feature, and intensity fraction features. Such features extracted are converted into an ensemble and tested with the network trained. With the ensemble generated, the method generates several possible ensembles according to the range values of coverage, mass index, and intensity factor to different values of tolerance in the range of +-10. Such combinatory samples are tested with the CNN where the intermediate layer convolves the LBP generated to the least dimension and in the RELU layer, the neuron uses a support vector machine algorithm in estimating Ensemble Centric Coverage Support Measure (ECCSM), Ensemble Centric Mass Support Measure (ECMSM) and Ensemble Centric Intensity Support Measure (ECISM) towards various classes. The output layer returns a set of values of ECCSM, ECMSM, and ECISM according to the number of mutations generated. With the set of values obtained, for each class, the method computes the value of disease attraction weight. Based on the disease attraction weight, the method identifies the class of brain image.

Algorithm

Given: CNN, Brain Image Bmg
Obtain: Class C
Start
Read CNN and Bmg.
Pimg = Preprocessing (Bmg)
Ensemble[LBP,CF,MI,IF] = Feature_Extraction (Pimg)

Ensemble set Es = $\underset{-10}{\overset{10}{Mutate\ with\ GA(LBP, CF, MI, IF)}}$

For each possible value of {CF,MI,IF}

Generate ensemble E = $\underset{-10}{\overset{10}{Construct\_Enseble(LBP, CF, MI, IF)}}$

AddtoEnsembleSetEs=$(\sum Ensembles \in Es) \cup E$
End
For each ensemble E
Apply SVM in Estimating ECCSM, ECMSM, ECISM.

$$ECCSM = \frac{\sum_{i=1}^{Size(C)} Dist(C(i).Coverage, E.Coverage)}{size(C)}$$

$$ECMSM = \frac{\sum_{i=1}^{Size(C)} Dist(C(i).MI, E.MI)}{size(C)}$$

$$ECISM = \frac{\sum_{i=1}^{Size(C)} Dist(C(i).IF, E.IF)}{size(C)}$$

[ECCSM, ECMSM, ECISM]= Test with CNN (E)
End
For each class C

$$\text{Compute DAW} = \frac{\frac{\sum ECCSM}{size(ES)}}{\frac{\sum ECMSM}{size(ES)}} \times \frac{\sum ECISM}{size(ES)}$$

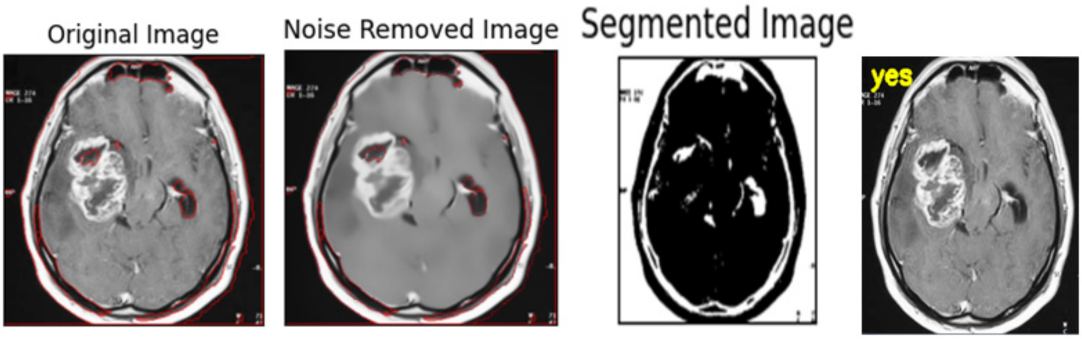

Fig. 6. Result of Brain Tumor Classification (Positive Class)
6(a): Original Image; 6(b): Noise Removed; 6(c): Segmented; 6(d): Classified

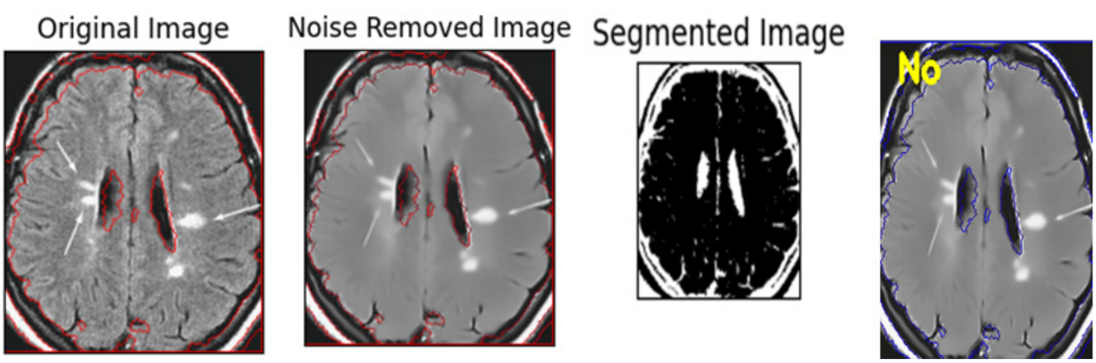

Fig. 7. Result of Brain Tumor Classification (Negative Class)
7(a): Original Image; 7(b): Noise Removed; 7(c): Segmented; 7(d): Classified

End
Class C = Choose the class and grade with maximum DAW.
Perform survival prediction according to the grade identified.
Stop

The above classification algorithm reads the input brain image and extracts the features concerned. With the features extracted the method test with the CNN by generating a combination of ensembles according to the range values of various features constructed with an ensemble, and optimizes the classification by computing the disease attraction weight. Based on the DAW value, a class with a higher DAW is identified as the target class. The method performs survival prediction according to the grade of the tumor class identified.

Survival Prediction

Survival prediction is the process of predicting the survival rate of the patient according to the measures returned by the proposed model for the given brain image. Accordingly, values obtained in the output layer of CNN at the test phase have been used in predicting the survival rate of the patient considered. The method obtains the values of Ensemble Centric Coverage Support Measure (ECCSM) and Ensemble Centric Mass Support Measure (ECMSM). The value of ECCSM represents how far the tumor is grown and ECMSM represents how badly the tumor has occupied the cells of the brain. Using these two values, the method computes the value of Survival Stage Support (SSS) towards each stage maintained. As the model maintains different survival classes, the method extracts the relevant features from each sample in the trained class of survival. With each feature extracted belonging to a specific survival class, the method computes the value of SSS. Based on the value of SSS, the method identifies the survival class of the person as result.

Algorithm

Given: Survival Class Set Scs, ECCSM, ECMSM, Brain Image Bmg
Obtain: Survival Class SC
Start
Read Scs, ECCSM, ECMSM, Bmg
Pimg = Preprocessing (Bmg)
Ensemble[LBP,CF,MI,IF] = Feature_Extraction (Pimg)
For each class s
For each ensemble E

$$ECCSMA=\frac{\sum_{i=1}^{Size(C)} Dist(C(i).Coverage, E.Coverage)}{size\ (C)}$$

Table 2. Analysis of Classification Accuracy

	Classification Accuracy in % vs No. of Samples 3000 samples	5000 samples	10000 samples
REPC	73	77	81
LINM	76	79	85
CNNBCN	79	83	88
RMFEA-CNN	84	89	98

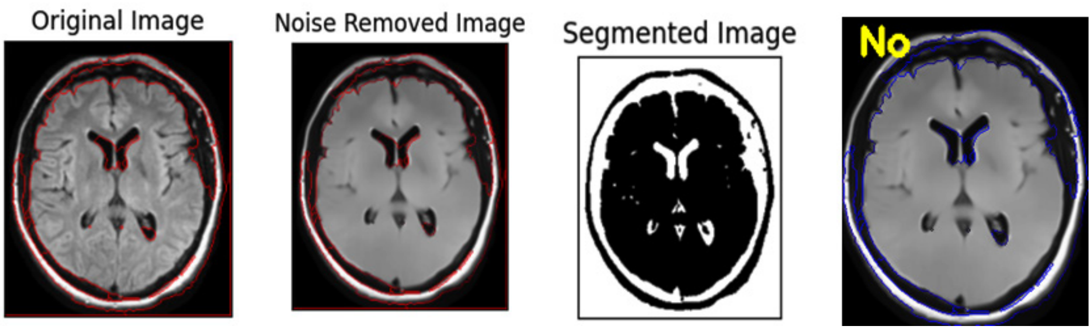

Fig. 8. Result of Brain Tumor Classification (Negative Class)
8(a): Original Image; 8(b): Noise Removed; 8(c): Segmented; 8(d): Classified

ECMSMA = $\frac{\sum_{i=1}^{Size(C)} Dist(C(i).MI, E.MI)}{size(C)}$

End

Compute cumulative ensemble similarity CES.

CES = $\frac{\sum ECCSMA}{size(S)} \times \frac{\sum ECMSMA}{size(S)}$

Compute SSS = Dist((ECCSM×ECMSM),CES)

End

Class C = Choose the survival class with maximum SSS.

Stop

The survival prediction algorithm estimates SSS values towards various survival classes and based on that the method selects a class with the maximum SSS value as the result.

RESULTS AND DISCUSSION

The proposed real-time multi-fractal ensemble analysis CNN-based brain image classification algorithm with SVM has been implemented and evaluated for its performance using the BRATS 18 data set. Obtained results are compared with the results of other approaches. A detailed analysis is given in this section.

The constraints considered for the performance evaluation are presented in Table 1, which has been used to analyze the performance under various parameters. The results obtained are presented in this section.

Figure 4 shows the result of preprocessing, segmentation, and classification produced by the proposed approach. Figure 4(a) shows the input image submitted and 4(b) shows the noise-removed image produced by HMA preprocessing. Similarly, Figure 4(c) shows the segmentation result and the classification result is shown in Figure 4(d).

Figure 5 shows the result of preprocessing, segmentation, and classification produced by the proposed approach. Figure 5(a) shows the input image submitted and 5(b) shows the noise-removed image produced by HMA preprocessing. Similarly, Figure 5(c) shows the segmentation result and the classification result is shown in Figure 5(d).

Figure 6 shows the result of preprocessing, segmentation, and classification produced by the

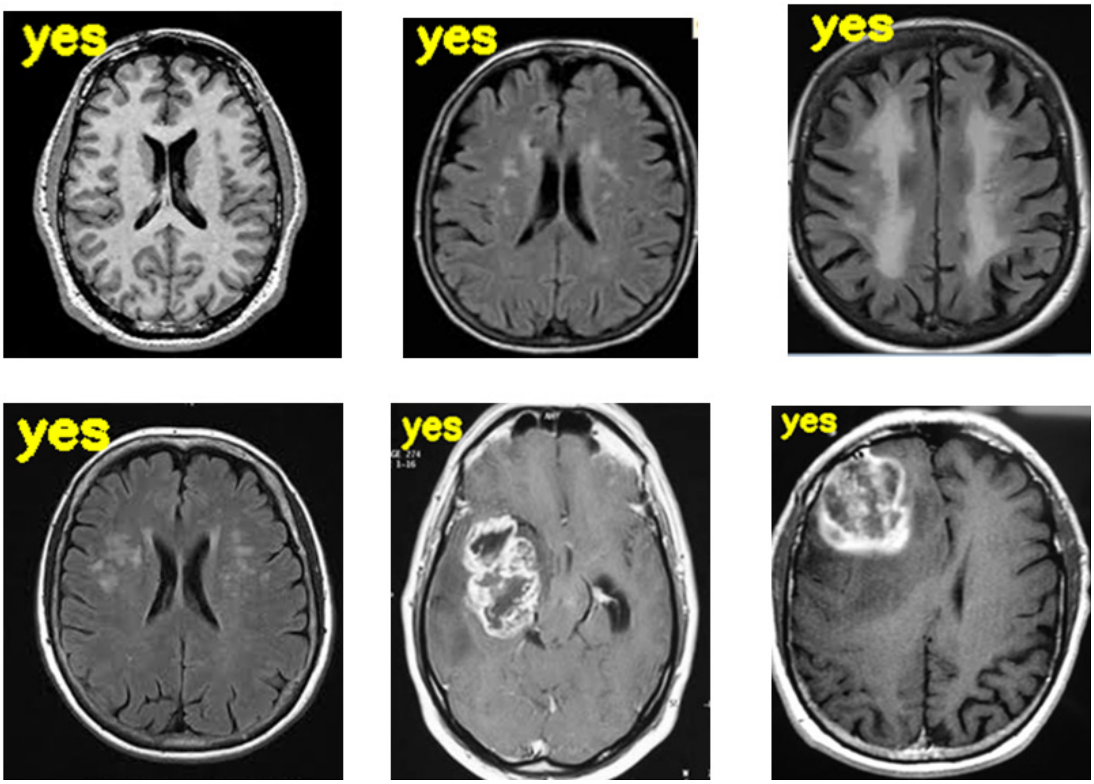

Fig. 9. Result of Multiple Classifications

proposed approach. Figure 6(a) shows the input image submitted and 6(b) shows the noise-removed image produced by HMA preprocessing. Similarly, Figure 6(c) shows the segmentation result and the classification result is shown in Figure 6(d).

Figure 7 shows the result of preprocessing, segmentation, and classification produced by the proposed approach. Figure 7(a) shows the input image submitted and 7(b) shows the noise-removed image produced by HMA preprocessing. Similarly, Figure 7(c) shows the segmentation result and the classification result is shown in Figure 7(d).

Figure 8 shows the result of preprocessing, segmentation, and classification produced by the proposed approach. Figure 8(a) shows the input image submitted and 8(b) shows the noise-removed image produced by HMA preprocessing. Similarly, Figure 8(c) shows the segmentation result and the classification result is shown in Figure 8(d).

The results produced by the proposed approach to classification have been presented in Figure 9. Each test sample has been classified and the result of classification is marked at the left corner of the image given.

Table 3. Analysis of False Classification Ratio

	False Ratio in Classification % vs No of Samples		
	3000 samples	5000 samples	10000 samples
REPC	27	23	19
LINM	24	21	15
CNNBCN	21	17	12
RMFEA-CNN	16	11	2

Table 4. Analysis of Time Complexity

	Time Complexity in Classification Seconds vs No of Samples		
	3000 samples	5000 samples	10000 samples
REPC	53	62	89
LINM	44	53	78
CNNBCN	41	47	72
RMFEA-CNN	21	28	33

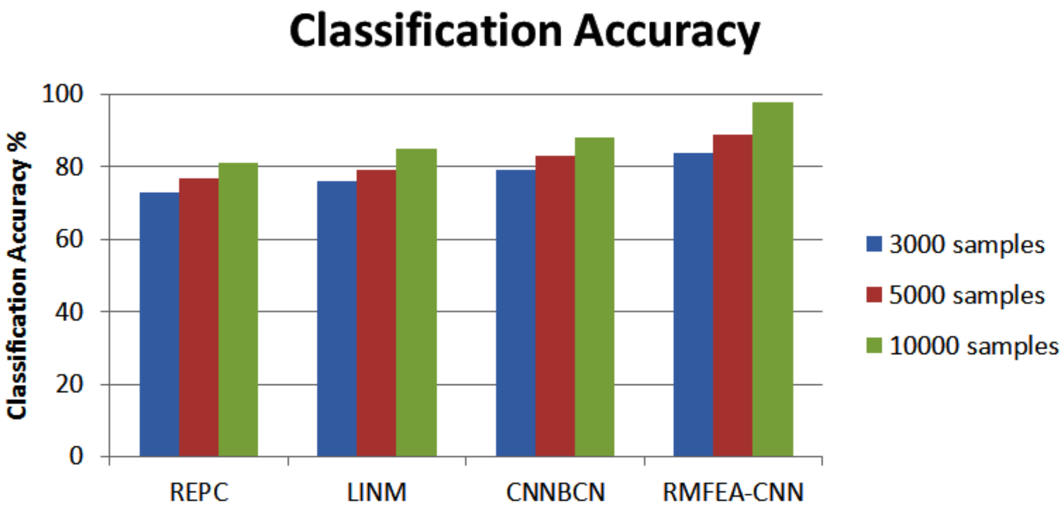

Fig. 10. Performance in Classification Accuracy

The performance of methods in classification accuracy is measured and presented in Table 2, where the proposed RMFEA-CNN approach has produced higher classification accuracy in all the test cases.

The performance of different methods of classifying brain images has been measured with the presence of a different number of samples. Obtained results are compared in Figure 10, which denotes the proposed RMFEA-CNN has produced higher accuracy than other approaches.

The false ratio introduced in brain image classification has been measured and presented in Table 3. The proposed RMFEA-CNN approach has produced less false ratio compared to others.

The ratio of false classification is measured for different approaches according to the number of samples in the data set. In each class, the proposed RMFEA-CNN has produced less false ratio compared to others.

The value of time complexity introduced by various approaches are measured and presented in Table 4. The proposed RMFEA-CNN has produced less time complexity compared to other methods.

The value of time complexity introduced by various approaches is measured and presented in Figure 12, where the proposed RMFEA-CNN has produced less time complexity than other approaches.

The performance of methods in survival prediction accuracy is measured and presented in Table 5, where the proposed RMFEA-CNN approach has produced higher survival prediction accuracy in all the test cases.

The performance of different methods of survival prediction has been measured with the presence of a different number of samples. Obtained results are compared in Figure 13, which

Table 5. Analysis of Survival Prediction Accuracy

	Survival Prediction Accuracy in % vs No of Samples		
	3000 samples	5000 samples	10000 samples
REPC	74	78	82
LINM	77	80	84
CNNBCN	79	83	88
RMFEA-CNN	86	90	97

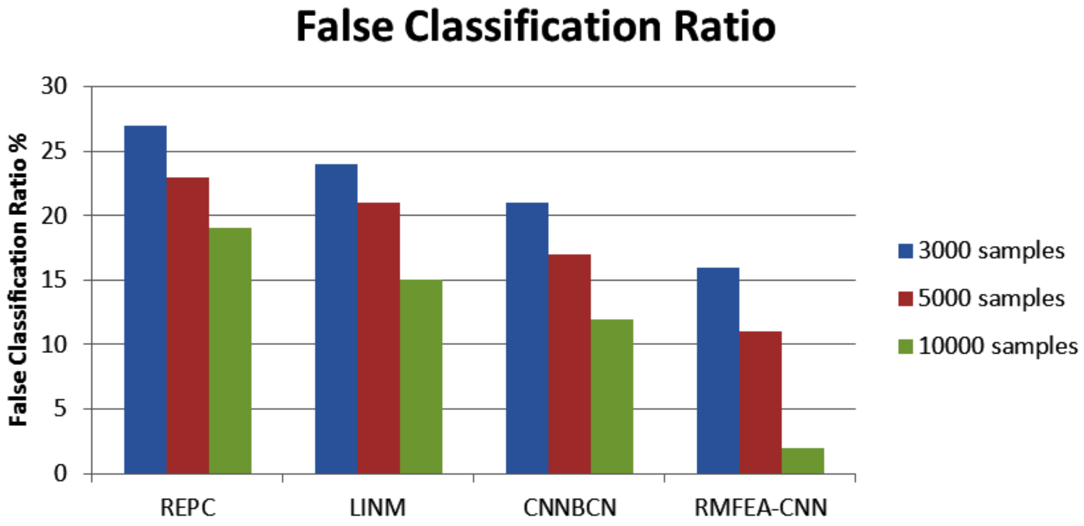

Fig. 11. Performance on False Classification Ratio

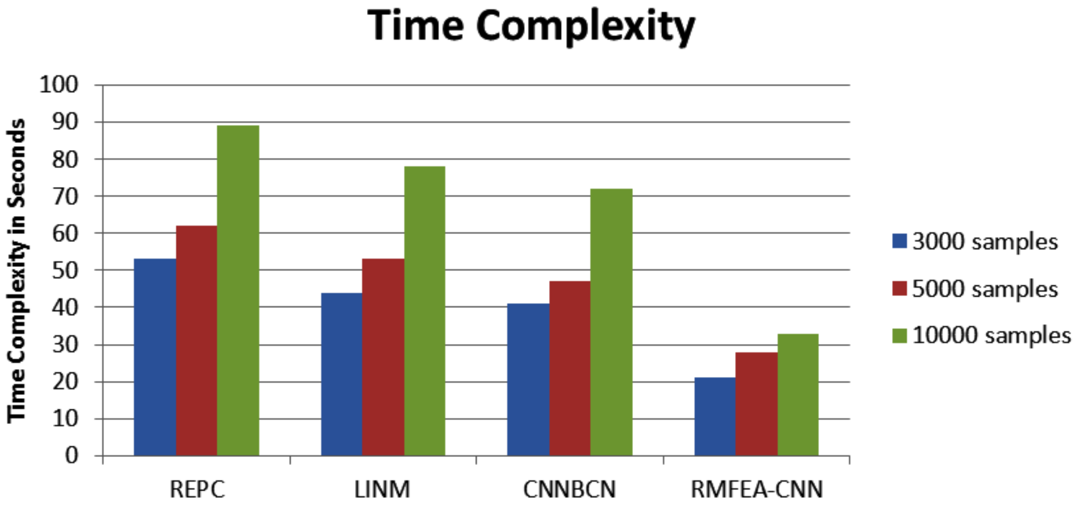

Fig. 12. Performance on Time complexity

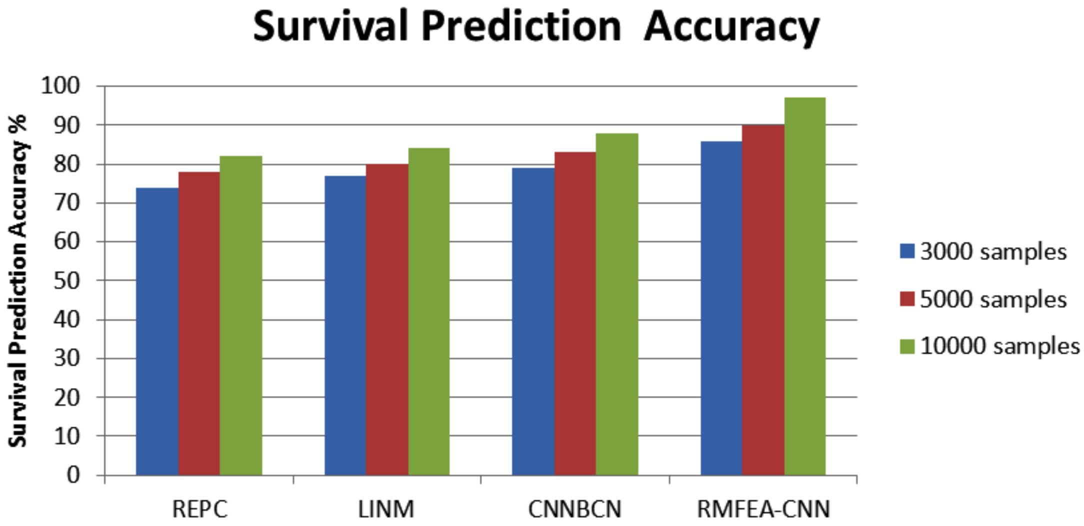

Fig. 13. Performance on Survival Prediction Accuracy

denotes the proposed RMFEA-CNN has produced higher accuracy than other approaches.

CONCLUSION

This article presented a novel real-time multi-fractal ensemble analysis CNN model for brain image classification with SVM. The proposed approach preprocesses the image by applying a histogram mean approximation scheme which removes the noise and extracts gray, binary, and texture features to compute the coverage, mass index, and intensity factors. Extracted features are trained with CNN and at the test phase, the method extracts the features and tests with the CNN trained. The intermediate layer performs convolution to reduce the feature size and estimates different support measures on coverage, mass index, and intensity factor. Using the support measures, the method computes the value of DAW to perform classification. Here support vector machine algorithm is used in optimizing the classification problem which estimates support measures for various features towards the different classes of brain tumors according to tolerance. The method performs survival prediction by computing SSS (Survival Stage Support) values toward various classes of survival grades. Based on the value of SSS, a specific class is identified. The proposed approach improves the performance of classification by up to 98% and reduces the time complexity by up to 21 seconds. In futute this method can be implemented for Satellite Image classification.

Conflicts of Interest

There is no conflicts of interest.

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