

HYBRID FIREFLY META OPTIMIZATION FOR BIO MEDICAL IMAGE PROCESSING USING DEEP LEARNING

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Abstract

Signal and image processing is a part of biomedical science. In that, Biomedical image processing have a great value such as recognition, segmentation and classification for disease diagnosis. In one part of biomedical science, brain tumor classification is considered with Magnetic Resonance Images (MRI) images using state of art models. Initially, the Convolutional Neural Network (CNN), Fast Convolutional Neural Network (FCNN), U-Net and M-Net model was considered for classification. Further, the Hybrid Firefly Meta Optimization (HFMO) is proposed for the better prediction purpose. The proposed work has three phases like normalization with augmentation, deep attention segmentation and classification. In the first phase, data augmentation is applied to increase the scope of the dataset. In the second phase, a deep attention technique is applied to concentrate on hotspot in the image during segmentation. Finally, a hybrid firefly optimization is applied to enhance the performance of the model in convolution neural network by backtracking the process. The measuring parameters like Dice coefficient, Jaccard index, Positive Projected Value (PPV), True Positive Rate and False Positive Rate were evaluated. The comparative analysis of various state of art models with proposed classifier were demonstrated. Thus the proposed technique produces the training accuracy as 98.62%, testing accuracy as 95.31 % and 1 % of loss.

Keywords: Augmentation, Central Nervous System, Dice Coefficient, Firefly optimization, Jaccard Index, Meta Learning, MRI.

1. INTRODUCTION

A brain tumor is dangerous illnesses that can upset both adults and children. More number of patients is identified with a brain tumor each year. Brain malignancies are classified as glioma, meningioma and pituitary. To extend the patients' lives, proper arrangement and system should be enhanced. MRI is the most effective method for noticing brain tumors (MRI). The MRIs yield a huge amount of image data. The radiologist inspects these pictures and understand the complexity of brain tumors and their potentials [7-10].

Deep learning is being used to predict various types of brain tumors. The primary goals are to achieve high levels of accuracy in brain tumor prediction. Deep learning approaches assist in the early identification of tumor. The abstraction of features is crucial in the grouping of brain tumors. The deep learning algorithm performs the feature abstraction and data reconstruction.

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As a result, the proposed system performs classification using deep learning algorithms such as Convolution Neural Network (CNN) and Transfer Learning (TL) [11-13].

The different types of tumor classification are Glioma tumor, Meningioma tumor, No tumor and Pituitary tumor. Glioma is a cancer that disturbs the brain and spinal cord. Meningioma is a brain cancer that arises from the membrane that surrounds the brain and spinal cord. It is the most prevalent type of primary brain tumor in adults. A pituitary tumor is a tumor that grows in the pituitary gland, which is situated nearby the brain and can affect hormone levels in the body [14-15].

The summary of the research work proposed as follows:

1. Data augmentation is applied to enhance the dataset by normalization, zoom, rotate and flip the image to improve the results during classification.
2. MRI segmentation techniques are used for analysing the brain images and perform the accurate segmentation of the regions by deep attention techniques.
3. The performance of state of art models were compared after the augmentation and segmentation.
4. The proposed Firefly Optimization Neural Network (FONN) performs the classification more accurate than other classification model by selecting the brighter parameters in the convolution layer.

The remaining part of the paper is decided in the subsequent way. Section 2 defines the literature review. Proposed methodology is described in Section 3. Section 4 shows the classification results of various state of art models and it is compared with the proposed work. Concluding remarks are drawn in Section 5.

2. Literature Survey

Various researchers introduced the methodologies and models to handle the MRI image dataset and perform the classification effectively. The following review suggests the readers to select the best model for classification.

The use of a reliable and automatic classification technique can lower human death rates. The large geographical and anatomical heterogeneity of the surrounding region of the brain tumor makes automatic classification of brain tumors. It proposes utilizing Convolutional Neural Networks (CNN) classification to detect brain tumors automatically. The deeper architecture design is done with little kernels. The load of the neuron is reported as tiny. Experiments reveal that CNN archives a rate of 97.5 % accuracy [1, 16].

Each traditional method for distinguishing brain tumors is to examine MRI pictures of the patient's brain. When dealing with big amounts of data, various kinds of technique were

used and it is a time consuming factor which leads to error. This is used to train CNN to identify different kinds of brain tumors: gliomas, meningioma, and pituitary tumors. CNN's architecture consists of flattening, convolutional and pooling layers. CNN was trained on weighted MRI images from brain tumor dataset. This gives the training accuracy of 98.51% and a validation accuracy of 84.19 % [2].

Various categorization approaches for brain MRI tumor classification have been identified. A hybrid technique was utilized to detect brain tumors using images. The Discrete Wavelet Transform (DWT) is used for feature mining, genetic algorithm for feature lessening, and a support vector machine (SVM) is used for brain tumor sorting. The Medical Image Repository (MIR) provides images that are classified as benign or malignant. The images are analyzed using the following parameters such as smoothness, entropy, root mean square error, and correlation [3].

For early detection of brain tumors, an automated method was proposed. This study presents an automated approach for discriminating between malignant and non-cancerous brain MRI. To segment possible lesions, several methods have been utilized. The shape, texture, and intensity of each applicant lesion are used to create a feature set. A Support Vector Machine (SVM) classifier with different cross validations are used to link the precision of the suggested structure on the features set [4].

A new method combines intensity, texture, and shape-based factors to diagnose tumors. The Internet Brain Segmentation Repository provided 140 brain images with tumors for the experiment. This technique was used on a greater database for more vigorous and effective prediction. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are used to compare nonlinear and linear techniques. PCA and LDA algorithms are used to decrease the sum of attributes needed for classification. This technique is superior because it examines the class variable and creates a smaller attribute set with more accuracy [5].

MRI is used to perform the medical imaging modalities for brain tumors, and it has been evolved into the primary analysis system for glioma management and examination. It was difficult to complete the process of segmenting and classifying brain tumors. Swarm intelligence has the potential to address a wide range of issues in a more effective and efficient manner. It uses the fuzzy brain-storm optimization algorithm for biomedical image segmentation and classification [6].

3. Proposed Methodology

The proposed work comprises three phases such as data augmentation, segmentation and classification. The disease diagnosis methods were given as per the following.

3.1 Data Augmentation:

The working flow of the data augmentation technique is given

in the Figure 1. Initially normalizing the images in a range of 0 to 1. The normalization process is given in the equation 1 and 2 and then performs the data augmentation. CNN allows identifying things even when located in dissimilar locations. Translation, viewpoint, size, and illumination can be an insensitive factor to CNN [17]. There is a need to extend the dataset, to avoid over fitting. Grayscale, vertical flips, random crops, horizontal flip and rotations are common augmentation techniques used to extend the dataset. It can simply dual or treble the number of training data [18-19].

$$x_{train} = x_{train_data} / 255. \text{Equation (1)}$$

$$x_{test} = x_{test_data} / 255. \text{Equation (2)}$$

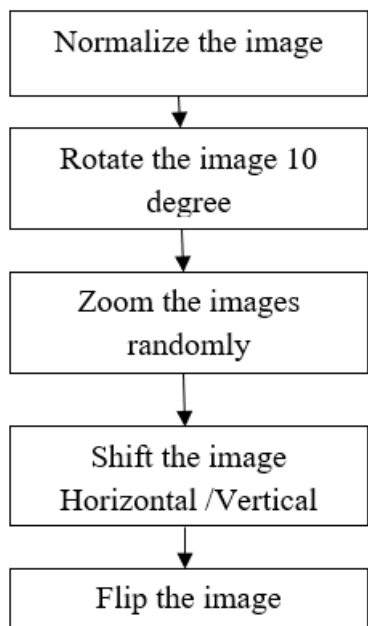


Figure 1. Data augmentation and normalizing the image for segmentation

After the augmentation, Brain Tumor MRI dataset contains the 3,275 MRI images with 4 categories such as Glioma, Meningioma, Pituitary and No tumor [20]. Table 1 shows the training and test data size considered for classification.

Table 1. Data set description after the

Dataset	Types of Tumor	Number of Images
Training	Glioma tumor	837
	Meningioma tumor	812
	No tumor	405
	Pituitary tumor	827
Testing	Glioma tumor	100

	Meningioma tumor	115
	No tumor	105
	Pituitary tumor	74

3.2 Meta learning framework for MRI Segmentation

The basic purpose of brain MRI segmentation is to split the image into clearly defined areas, each of which is made up of a group of pixels with comparable intensities, textures, or neighborhoods. In the proposed framework, reconstructed images from the reconstruction meta-learning phase are first received by the segmentation module. It has the basic picture preparation procedures includes filtering and resolution improvement. The meta-learning segmentation framework receives the preprocessed picture from the previous steps. The state of art models such as Convolutional Neural Networks (CNN), Fast Convolutional Neural Networks (FCNN), M-Net, U-Net and the Fuzzy C-mean framework are used to segment the MRI. From the analysis U-Net model is selected as an optimized model after performing the Meta learning approach [21]. The steps involved in meta learning framework is explained below.

3.2.1 Steps involved in Meta learning framework

1. Collect the images after augmentation
2. Prepare the dataset for optimization
3. Use the callback function to select the optimized parameters such as epoch and learning rate.
4. A neural network is a computer program that attempts to simplify human brain actions. In deep neural networks, the same process selectively concentrating on a few significant things while disregarding others. The deep attention mechanism is used to concentrate on a significant part of the brain image.
5. Deep attention mechanism employs an encoder-decoder design. The encoder design extracts features from a convolutional layer, allowing the decoder's attention to be focused on spatially relevant areas of the input image.

$$\text{Vector (v)} = \sum_{a=1}^{\infty} w_{ab} h_a \quad \text{Equation (3)}$$

In the above equation w_{ab} represents the weight and h_a is an input calculated by using a softmax activation function as given in equation (3).

$$A = \exp(FCCN)_{ab} \quad \text{Equation (4)}$$

$$B = \exp(FCCN)_{bc} \quad \text{Equation (5)}$$

$$w_{ab} =$$

$$\frac{A}{\sum_{k=1}^T B} \quad \text{Equation (6)}$$

Where A is a variable which contains output score of feedforward neural network between a and b. B is a variable which contains output score of feedforward neural network

between b and c.

Wab specifies the weights of softmax function.

6. Compare the performance of state of art models with deep attention mechanism.

7. Apply the Model Agnostic Meta-Learning (MAML) to select the best model based on the performance.

$$\Theta = \{ m1,m2,m3,m4...mn\} \quad \text{Equation (7)}$$

$$P(Ti) = P(T) \quad \text{Equation (8)}$$

Where Θ represents the number of models from 1 to n as given in equation (7). P (Ti) represents the performance of current task which equates the performance of previous task P(T) as given in equation (8).

The performance is evaluated using the following equation (9)

$$e = \sum_{m=1}^n P(M1, M2M3 \dots M4) \quad \text{Equation (9)}$$

(9)

Where e represents the evaluation of various model based on the training accuracy, training loss, testing accuracy and testing loss. P represents the performance of model. The overall steps involved in the process are in Figure 2.

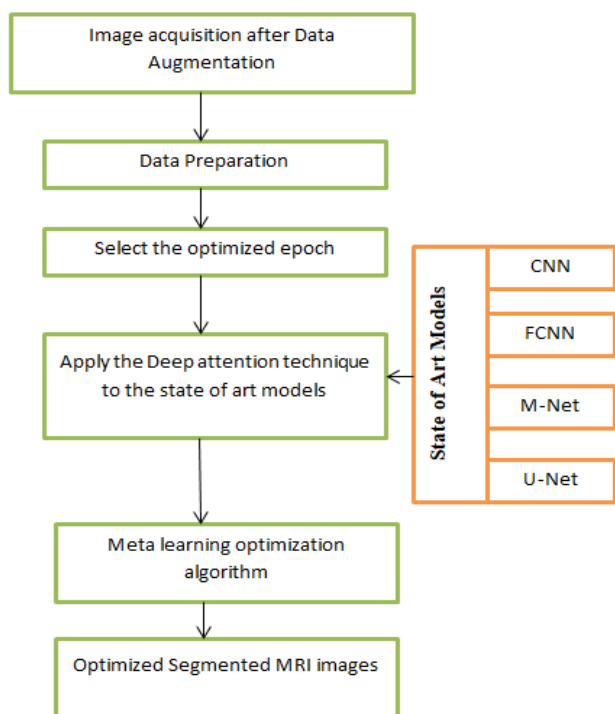


Figure 2. Selection of deep attention technique for the models and optimized MRI images

3.3 Firefly Optimization Algorithm (FOA):

Optimization is a problem of identifying the standards for a variables and these problem is expressed using scientific terms when a decision needs to be made. It is fully depends based on the behavior of the problem. A simple algorithm will be used to solve the linear programming problem.

Sometimes, numerous complications require superior care to solve deterministic methods [6]. Metaheuristic algorithms are used to recover the excellence of the solution with some assets. A solution does not affected by the working of optimization algorithm. Firefly is an algorithm introduced by Yang et.al which mimics the behavior of firefly [7]. There are three rules will be followed by firefly. First rule is any firefly can be attracted by the brighter one. The second rule is identifying the brighter firefly using encoded objective function. The third rule, firefly will move randomly when there is no brighter one [22].

$$I = S_i e^{-cd^2} \quad \text{Equation (10)}$$

Where I represent the intensity of light, Si represents the source point intensity represents the light absorption coefficient and d represents the distance as given in equation (10). This also represented as given in the equation (11).

$$e^{-cd^2} = \frac{1}{1+cd^2} \quad \text{Equation (11)}$$

The intensity of the light is represented in equation 12.

$$I = \frac{S_i}{1+cd^2} \quad \text{Equation(12)}$$

The attractiveness of the firefly is considered as A and represented in the equation (13).

$$A = \frac{A_i}{1+cd^2} \quad \text{Equation (13)}$$

where A_i is the attractiveness at $d=0$.

$$p1 = (m1,m2,m3,\dots,mn) \quad \text{Equation (14)}$$

Where p1 represents the single firefly in a population and m1, m2, m3,...mn represents the various locations of firefly visited previously. When a firefly situated in p1 is optimistic than another firefly p2, then p2 will move towards p1. The location update of the firefly is given in the equation (15).

$$p2 = p2 + A (p1 - p2) + \alpha \delta \quad 0 < \alpha < 1, 0 < \delta < 1$$

Equation (15)

Where p2 represents the firefly move towards brighter firefly p1, A represents the attractiveness, $\alpha \delta$ represents the random numbers.

3.4 Proposed Hybrid Firefly Meta Optimization Algorithm:

The proposed work is comprised of firefly and Model Agnostic Meta-Learning approach to perform the segmentation and classification. It uses the deep attention technique to segment the images and selects the best state of art model from list such as CNN, FCNN, M-Net and U-Net. A CNN is different form of artificial networks used for image recognition and classification. FCNN is used to compute net masses between the output and hidden layers in single epoch. M-NET is used to split the human brain regions from MRI. The novel techniques are used to express 3D context information of a particular slice in 2D slice. The M-networks with 3D data uses 2D convolution which saves memory. With

the purpose of providing a full-resolution semantic prediction, a U-Net augments the normal CNN design by adding a comparable expanding path. The goal is to create segmentation images that highlight specific features and objects in the image [23].

Finally, it uses the firefly optimization algorithm to select the optimal parameters for the models selected in segmentation. The following hybrid equation (16 &17) is used to analyse the performance.

$$y=wx+b \tag{Equation (16)}$$

$$y=A/(\sum_{K=1}^T B) \ x + p2+A(p1-p2)+\alpha\delta \tag{Equation (17)}$$

Where the w represents the weight calculated based on the Meta learning optimization and then firefly optimization solution chooses the best one from the population.

Initially there are four samples collected from the database and shown in Figure 3. The glioma tumor, meningioma tumor, pituitary tumor and no tumor is given below.

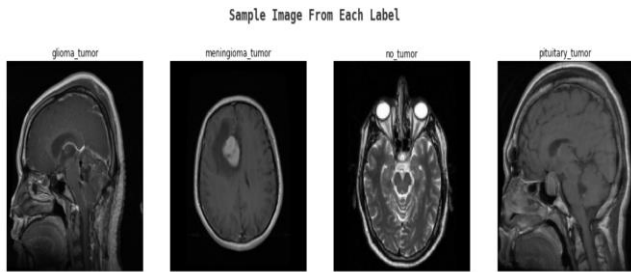


Figure 3: The sample images from each category

The above Figure 4 shows the architecture of proposed convolution layer after applying the Firefly optimization. Initially, the input image is collected from dataset and the conv2D layer is used to handle the input image with the size of (64, 3, and 3).

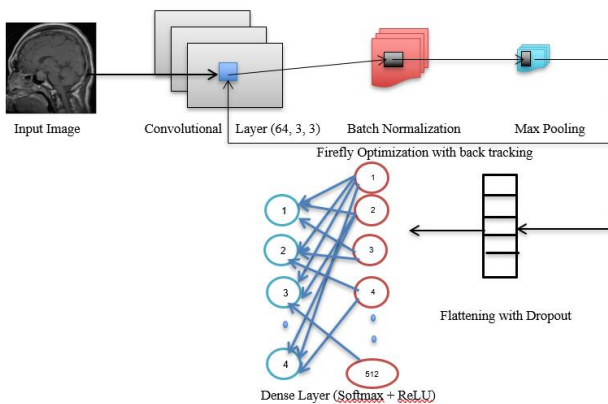


Figure 4: Architecture of Proposed Convolutional Layer

The batch normalization is applied to standardize the input for each mini batch. Next, the max pooling is applied to reduce the size of the matrix and the same process will be repeated for N number of times until it gets the brighter model. Finally, the flattening technique is applied before

classification. The fully connected dense layer uses the epoch, weight, bias and learning rate as parameters and activation function like softmax and ReLU is applied to perform the classification. Next, the working flow of the model is given in Figure 5 and the proposed model FONN internal structure is shown in the Figure 6.

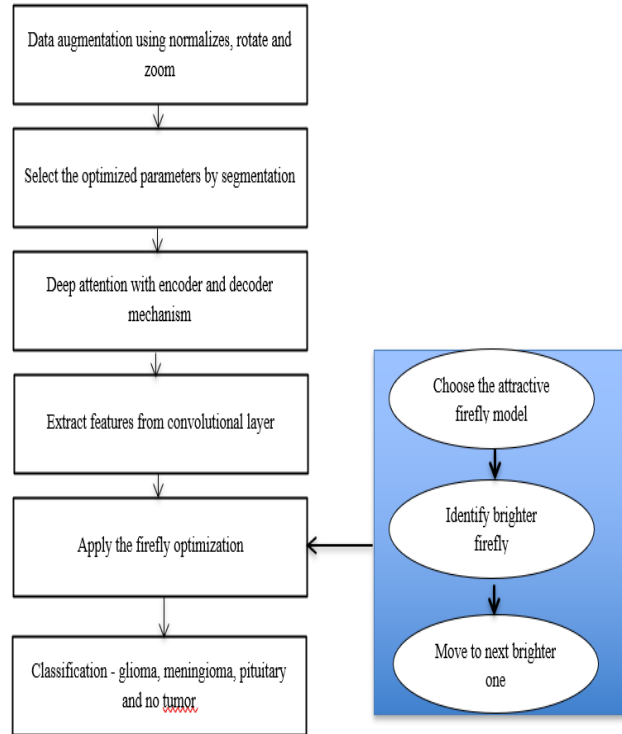


Figure 5: Working flow of the Deep Attention with Firefly Optimization in tumor prediction

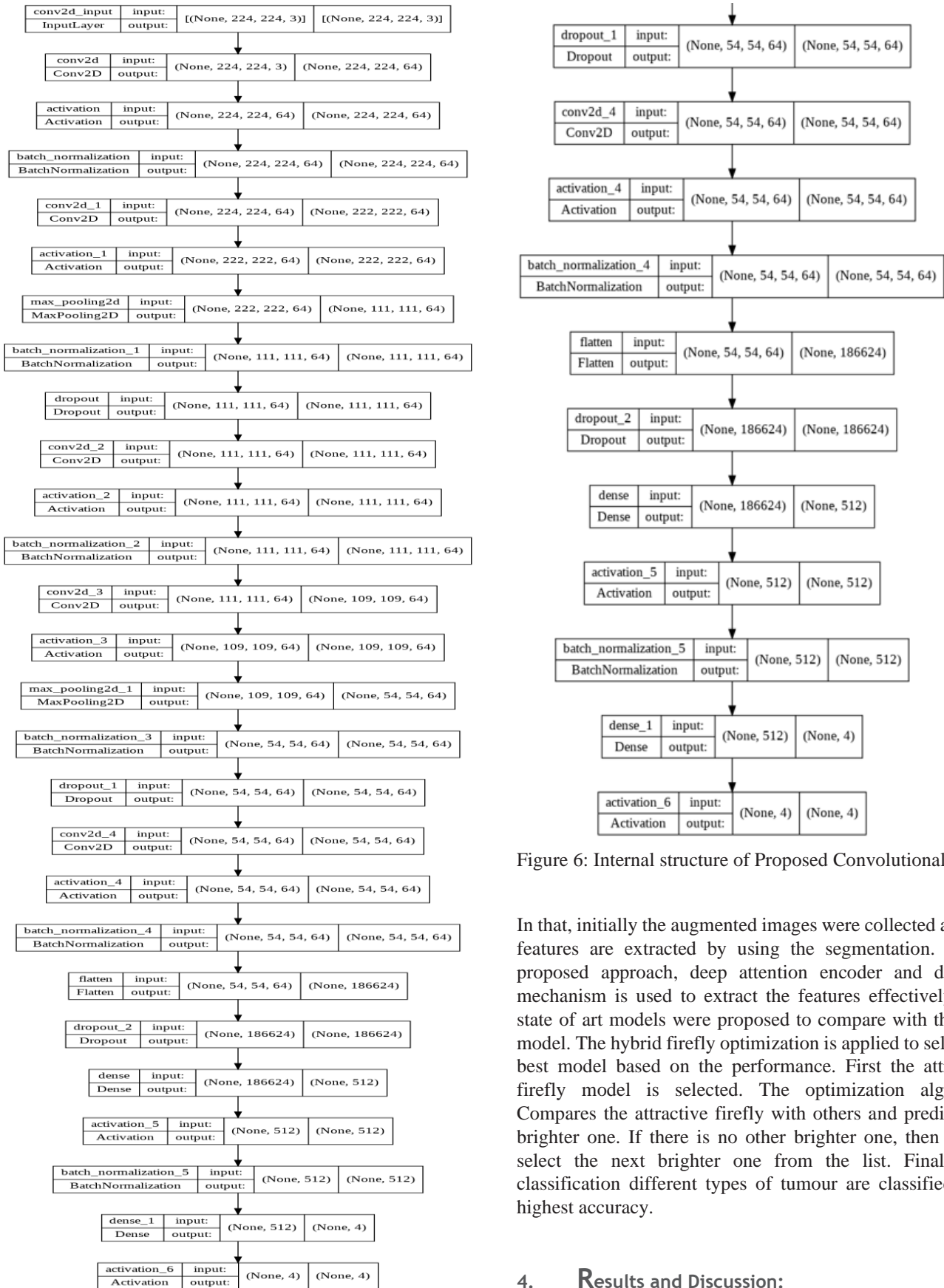


Figure 6: Internal structure of Proposed Convolutional Layer

In that, initially the augmented images were collected and the features are extracted by using the segmentation. In the proposed approach, deep attention encoder and decoder mechanism is used to extract the features effectively. The state of art models were proposed to compare with the new model. The hybrid firefly optimization is applied to select the best model based on the performance. First the attractive firefly model is selected. The optimization algorithm Compares the attractive firefly with others and predicts the brighter one. If there is no other brighter one, then it will select the next brighter one from the list. Finally the classification different types of tumour are classified with highest accuracy.

4. Results and Discussion:

The most well-known evaluation measure is used to identify the quality of two binary label masks. In this, Hp represents

human prediction and MP represented by deep learning methods [8].

The dice coefficient is calculated using Equation (18).

$$D = \frac{2(H_P \cap M_P)}{|H_P| + |M_P|} \text{Equation (18)}$$

The overlap measure has a range of values between 0 and 1, with 0 indicating no match and 1 representing that the actual and predicted are equal. When comparing two binary label masks, the Jaccard index is employed as a similarity metric and expressed in Equation (19).

$$J = \frac{(H_P \cap M_P)}{|H_P| + |M_P| - (H_P \cap M_P)} \text{Equation (19)}$$

The Positive Projected Value (PPV) is the ratio of correctly classified as positive values to the addition of correctly classified as positive values and false positives and expressed as Equation (20).

$$PPV = \frac{\text{Correctly classified (positive)}}{\text{True Positive} + \text{False Positive}} \text{Equation (20)}$$

The Lesion True Positive Rate (LTPR) is demarcated as the ratio of correctly classified as positive values to the sum of correctly classified as positive values and false negatives which can be expressed in Equation (21).

$$LTPR = \frac{\text{Correctly classified (positive)}}{\text{True positive} + \text{False Negative}} \text{Equation (21)}$$

Furthermore, the Lesion False Positive Rate (LFPR) is defined as the ratio of false positives per lesion to the sum of false positives and true negatives which can be expressed in Equation (22).

$$LFPR = \frac{\text{False Positive}}{\text{False positive} + \text{True Negative}} \text{Equation (22)}$$

Table 2 shows the performance of the various models and its accuracy and loss. From the observation, CNN model produces the training accuracy by 85.23 % and testing accuracy as 84.26%. The loss is observed as 40% for both training and testing. The FCNN has the training accuracy as 86.11 % and 80.27%. The training loss is 51 and 60% respectively for both training and testing loss. The M-Net model accuracy is 84.35% and 82.33%. The loss of M-Net model is represented as 71% and 67 % respectively. U-net model performs well than other classification models which produces the training accuracy as 89.62 % and testing accuracy as 88.42% with a loss of 20%. Finally the hybrid firefly meta algorithm produces the training accuracy as 98.62 % and testing accuracy as 95.31% with the loss of 1%. From the observation the proposed model gives an optimized result than other state of art models.

Table 2: Summary of results in the existing methods vs Hybrid Firefly Algorithm

Models	Training Accuracy (%)	Testing Accuracy (%)	Training Loss (%)	Testing Loss (%)
CNN	85.23	84.26	0.40	0.41
FCNN	86.11	80.27	0.51	0.60
M-Net	84.35	82.33	0.71	0.67
U-Net	89.62	88.42	0.12	0.23
Hybrid Firefly meta Algorithm	98.62	95.31	0.01	0.01

From the Table 3, CNN has 79.21 % as dice coefficient, 80.11 % as jaccard index, 82.36% as PPV, 83.33% as TPR and 5.2 % as FPR. But in Hybrid Firefly Meta Optimization

Algorithm produces the better result than other models. It produces the 96.45 % as dice coefficient, 98.45 % as jaccard index, 97.67% as PPV, 97.67% as TPR and 0.1 % as FPR value.

Table 3: Performance analysis of state of art models with proposed work

Models	Dice coefficient (%)	Jaccard index (%)	PPV (%)	TPR (%)	FPR (%)
CNN	79.21	80.11	82.36	83.33	5.2
FCNN	82.34	83.75	84.12	85.12	4.3
M-Net	86.32	84.21	83.45	84.44	4.1

U-Net	87.12	85.53	84.42	85.65	3.2
Hybrid Firefly Meta Optimization Algorithm	96.45	98.45	97.67	97.67	0.1

Figure 7 represents the training and validation accuracy of CNN. From the observation, training and testing accuracy gets convergence during the epoch 12. The maximum number of epochs is 20 which are taken based on the keras callback function. Initially, the performance of the model is very low. But, after epoch 7, the performance of the CNN gradually increased.

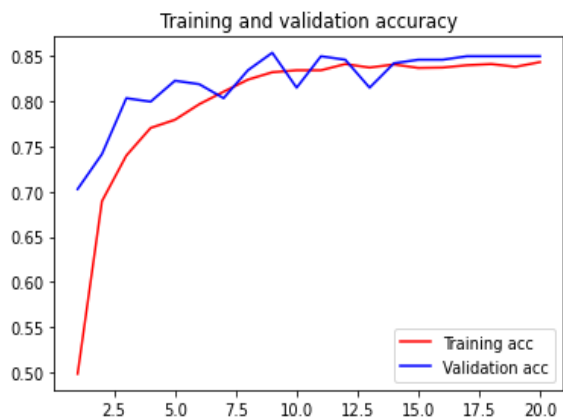


Figure 7. Training and validation accuracy of CNN

Figure 8 represents training and validation loss of CNN. From the observation, there is a less chance of overfitting and under fitting. Even though, the CNN perform well without overfitting. But there is a huge amount of loss which degrades the performance.

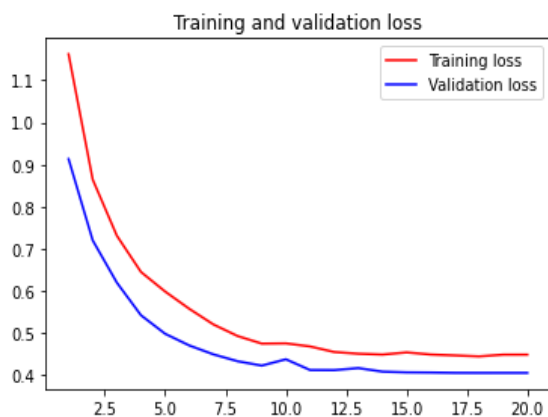


Figure 8: Training and validation loss of CNN

Figure 9 represents the training and validation loss of Hybrid Firefly Meta Optimization. The training accuracy is 98.62 % and testing accuracy is 95.31% .The performance of the model increases from thirteenth epoch and it's free from overfitting and under fitting after the implementation of

keras call back function.

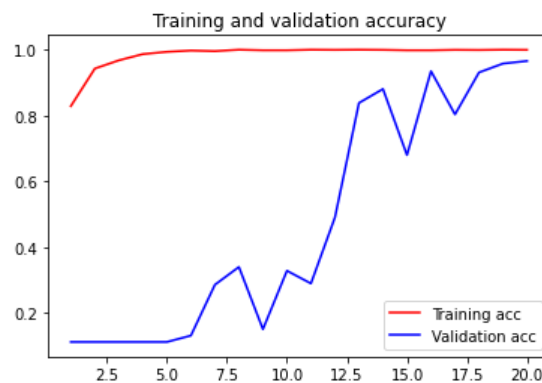


Figure 9: Training and validation accuracy of Deep Attention with Firefly Optimization

Figure 10 represents the training and validation loss of Hybrid Firefly Meta Optimization. Initially the loss of training data is very high compared with test data. After performing the optimized epoch selection, the model gets convergence from twentieth epoch. Finally the model has less than 1 % of loss compared with other state of art models.

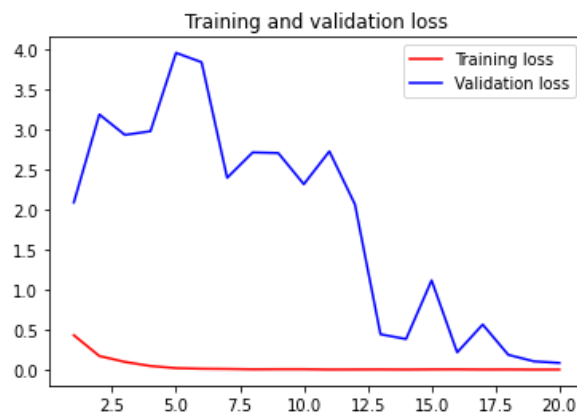


Figure 10: Training and validation loss of Deep Attention with Firefly Optimization

5. Performance Analysis

In this section, performance analysis based on the accuracy, precision and recall were observed. The evaluation is done during the epoch from 20 to 100 by applying the keras callback and early stopping methods. The accuracy, precision and recall of state of art models and proposed work were represented in the Table 4, Table 5 ,Table 6 and Figure

7, Figure 8 and Figure 9 respectively. From the analysis, the Hybrid Firefly Meta Optimization Algorithm (HFMOA) gives the accuracy of 95.31% comparatively greater than other models. In the analysis, some hybrid neural network models CNN, FCNN, M-Net, CNN+LSTM, BiLSTM, CNN+ BiLSTM, RNN+LSTM and U-Net were used to compare with proposed models as given in Figure 7.

Table 4: Accuracy of state of art models with proposed work

Models	Accuracy (%)
CNN	88.3
FCNN	91.1
M-Net	89.3
CNN +LSTM	91.2
BiLSTM	87.2
CNN+ BiLSTM	90.3
RNN+LSTM	85.4
U-Net	90.4
CNN + HFMOA	95.31

Table 5: Precision of state of art models with proposed work

Models	Precision (%)
CNN	86.6
FCNN	89.2
M-Net	88.2
CNN +LSTM	90.1
BiLSTM	86.1
CNN+ BiLSTM	87.3
RNN+LSTM	81.5
U-Net	88.1
CNN + HFMOA	93.3

Table 6: Recall of state of art models with proposed work

Models	Recall (%)
CNN	87.2
FCNN	90.3
M-Net	88.1
CNN +LSTM	85.3
BiLSTM	82.4
CNN+ BiLSTM	88.3
RNN+LSTM	89.5
U-Net	84.4

CNN + HFMOA	92.2
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In the figure 11, the accuracy of state of art models CNN, FCNN, M-Net, CNN+LSTM, BiLSTM, CNN+ BiLSTM, RNN+LSTM and U-Net and CNN + HFMOA were 88.3 %, 91.1%, 89.3%, 91.2%, 87.2%, 90.3%, 85.4%, 90.4% and 95.31% respectively.

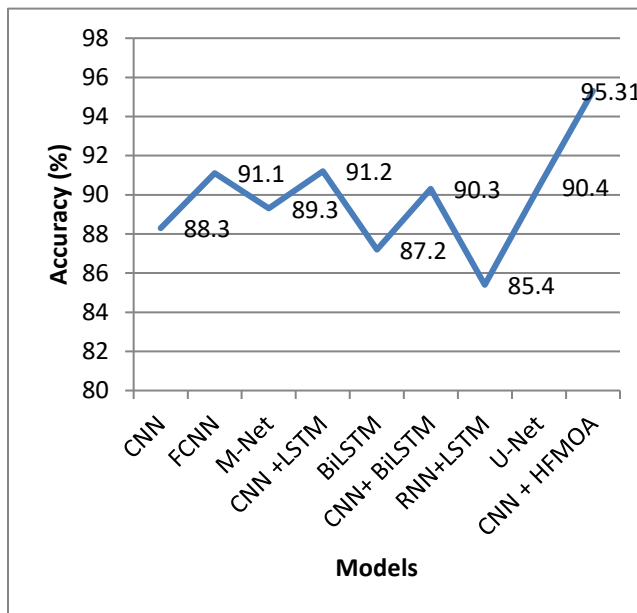


Figure 11: Accuracy of proposed model compared with state of art models

The precision of state of art models CNN, FCNN, M-Net, CNN+LSTM, BiLSTM, CNN+ BiLSTM, RNN+LSTM and U-Net and CNN + HFMOA were given in Figure 12 as 86.6%, 89.2 %, 88.2%, 90.1%, 86.1%, 87.3%, 81.5%, 88.1% and 93.3% respectively. Thus the precision of proposed model was performed better than the other models in the prediction of brain tumor.

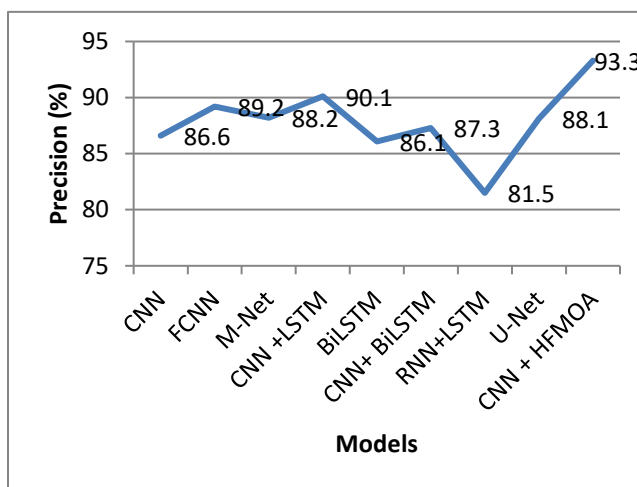


Figure 12: Precision of proposed model compared with state of art models

The recall of state of art models CNN, FCNN, M-Net, CNN+LSTM, BiLSTM, CNN+ BiLSTM, RNN+LSTM and

U-Net and CNN + HFMOA were given in Figure 13 as 87.2%,90.3%,88.1%, 85.3%,82.4%,88.3%,89.5%,84.4% and 92.2% respectively. From the analysis, the proposed work performs better than the existing models.

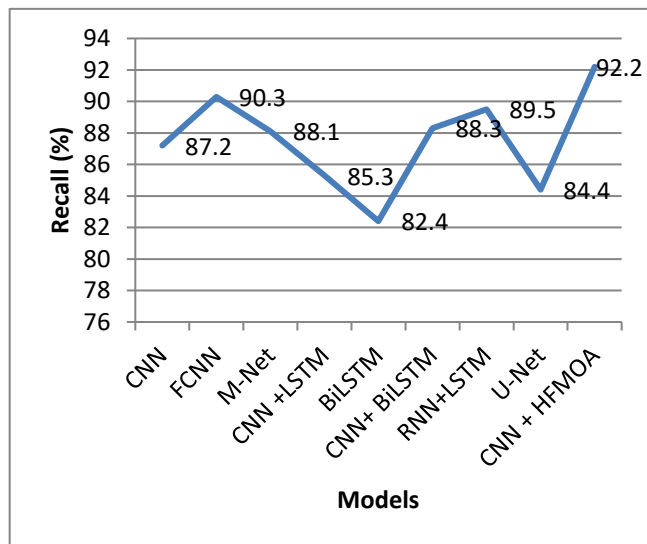


Figure 13: Recall of proposed model compared with state of art models

Finally, Gradient-weighted Class Activation Mapping (Grad-CAM) develops a rough localization map emphasizing the essential regions in the image for predicting the idea by using the gradients to the final convolutional layer. The sample Grad-CAM image is mainly used to highlight the hotspot to the medical professionals.

6. Conclusion

In this paper, a novel method called Hybrid firefly Meta Optimization is proposed for the better performance to diagnose the disease with highest accuracy. There are three techniques were used to detect the tumor in brain MRI images. First method is data augmentation for creating the more number of training and test data. The horizontal, vertical flip images and rotated images are considered after normalization. In the second technique, a Model Agnostic Meta-Learning model was used to select the best state of art models from the analysis. During this phase, a deep attention mechanism was used to consider the suspect region of the image for analysis. In the third technique, a hybrid firefly optimization technique was used to select the optimized model for the problem arises in previous stages. During this stage, the proposed firefly chooses the optimal model for better prediction. From the analysis, the proposed algorithm produces the better results such as 96.45 % as dice coefficient, 98.45 % as jaccard index, 97.67% as PPV, 97.67% as TPR and 0.1 % as FPR value.

Declarations

Consent for publication

I give my consent for the publication of identifiable details, which can include the datasets and images used for analysis during this study, is available in the Kaggle repository and this investigation was not done on live vertebrates and/or higher invertebrates. (<https://www.kaggle.com/code/omarsalahhemed/brain-tumor-detection-with-2-dataset/data>).

Competing interests

The authors declare no competing interests.

Conflict of interest

I declare that the authors have no competing interests as defined by Springer, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

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