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Detection of Brain Tumor Types based on Fanet Segmentation and GLRLM with Ensemble Learning

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***Abstract*— Enhancing the prognosis of brain tumors through early detection is crucial for enhancing patient survival through improved treatment results. It is a challenging task to manually assess the Magnetic Resonance Imaging (MRI) generated on a regular basis in the clinic. Thus, more accurate computer-aided techniques are desperately needed for early tumor diagnosis. Tumor identification, segmentation and classification procedures are part of computer-aided brain tumor diagnosis from MRI. In this model, uses the RS-ESIHE pre-processing approach to acquire enhanced MRI images. Pre-processed MRI is segmented using the FANET and segmented images are extracted using the GLRLM technique. The ensemble learning classifier is trained to predict different types of brain tumors. This proposed model achieves performance metrics of 98.5%, 97.5%, 96.8%, 1.5%, and 99% for Accuracy, precision, F1-Score, error and specificity. The comparisons are conducted between the assessed values and existing approaches like Mask-RCNN, DCNN, and SENET. Thus, the detection of brain tumor types based on FANET segmentation and GLRLM with an ensemble learning classifier performs better prediction than the existing model.**

***Index Terms*— Brain tumors, MRI, RS-ESIHE, FANET, GLRLM, RBFN, DBN, Bi-GRU.**

I. INTRODUCTION

A brain tumor is a mass that directly impacts human life based on the development of the brain from the tissues surrounding the skull or the brain. These brain tumors rub against one another as it grow irregularly [1]. Human manifestations of these conditions include headaches, dizziness, fainting episodes, paralysis, and other symptoms. Malignant tumors, in contrast to benign tumors, grow unevenly and cause tissue damage. In common, surgical techniques are favored when treating brain tumors [2]. On the other hand, alternative treatments, such as radiation, medicine, etc., are utilized, usually surgery is the best way to remove a brain tumor which is located at a crucial place. several non-invasive medical imaging technology types, such as MRI, ultrasound, CT scan, PET, SPECT, and X-ray are used for detecting the cancer. When it comes to magnetic resonance imaging (MRI), medical diagnosis systems (MDS) performs effective than computed tomography (CT) since it allows for a higher contrast between the body's various soft tissues [3]. A strong magnetic field is used in an MRI scan to identify radio frequency pulses and provide detailed images of the body's interior organs, bone, soft tissues, and other structures. The best method for detecting brain tumors is the MRI based models. Many studies have been conducted by

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different researchers to identify and categorize brain tumors [4]. A fuzzy C-Means clustering technique that provides many groups from the input images and detects brain tumors from MRI by using adaptive threshold segmentation to determine any kind of extracted tumors . Due to its size, shape, location, and appearance, the prediction of the brain tumor is challenging for diagnosing. Hence this proposed detection of brain tumor types based on FANET segmentation and GLRLM with Ensemble learning to identify the brain tumor early. The main contributions of the proposed model are

- Detection of brain tumor types based on FANET segmentation and GLRLM with Ensemble learning is designed.
- RS-ESIHE method is used for preprocessing the collected MRI images to enhance the pixel-level quality of an image.
- For segmentation, the FANet employs a single end-to-end trainable network that enables information propagation based on a feedback mechanism to segment the tumor region.
- GLRLM technique is employed to extract features from the images for texture analysis to train the classifier
- Ensemble learning algorithm based on RBFN and DBN with Bi-GRU is used for predicting the brain tumor types.

The sections of the paper are as follows: Section 2 investigates the various articles related to brain tumor diagnosis. The proposed method is briefly described in Section 3. Experimental findings for the proposed model are provided in Section 4 and the research article is concluded in the last section.

II. LITERATURE REVIEW

Many articles relating to brain detection are explored in this section, and a few of these works are discussed below with limitations.

Gull et al. [5] developed an extensive analysis and comparison of different automated approaches for classifying brain tumors, based on machine learning and deep learning algorithms for MRI-based brain tumor identification. This work employs a variety of machine learning (ML) and deep learning (DL) techniques, such as fuzzy C-means, support vector machines, K-nearest neighbor, decision trees, G-convolutional neural networks, artificial neural networks (ANN), deep neural networks (DNN), conditional random field-recurrent neural networks (CRF-RNN), Naive Bayes, etc. Arunkumar et al. [6] designed by utilizing the greatest characteristics for preparing to disclose a brain tumor case, ANN from MR images was employed to create an enhanced automated brain tumor segmentation and identification system that eliminates the requirement for human intervention. It provided three significant areas of improvement for the brain tumor segmentation method that may be used to identify the exact district region of an MR brain tumor.

Alam et al. [7] introduced a model that uses the enhanced fuzzy C means (TKFCM) algorithm and template-based K means to identify brain cancers in humans in magnetic resonance imaging (MRI) scans. The updated membership was determined by the fuzzy C-means (FCM) algorithm, which used the distances between cluster data points and the cluster centroid to reach its optimal outcome. Lastly, by updating membership functions that are derived based on the various properties of the tumor image, such as energy, contrast, dissimilarity, entropy, correlation and homogeneity, the improved FCM clustering algorithm was applied for tumor position detection.

Bangare et al. [8] designed several preprocessing methods, including as grayscale, thresholding, edge detection, and 3D model generation and reconstruction, are used to identify brain tumors. The tumor are seen in three dimensions and are further classified into three categories. The purpose of this concept is to serve as an evaluation instrument for brain tumor diagnosis. This research develops a two-dimensional image of a patient's tumor at every stage. Because the OTSU algorithm computes an optimum threshold value quickly, it has been utilized to calculate the threshold. The sharp shifts are revealed using the Sobel edge detection method.

Arif et al. [9] developed an MRI sequence's images were used as the input image for a brain tumor segmentation and detection algorithm, which located the tumor's location. The primary objective is to categorize the brain as healthy or as having a brain tumor. In order to enhance performance and streamline the medical picture segmentation process, a deep learning classifier and Berkeley's wavelet transformation (BWT) have been the foundation of the suggested system's research. Utilizing the gray-level-co-occurrence matrix (GLCM) approach, significant features are identified from each segmented tissue and then optimized using a genetic algorithm.

Majority of the articles evaluated above are related to brain tumour detection. The large volume of data needed to train DNNs are its greatest flaw [5]. The requirement for substantial data sets and computer power is one of the primary problems with neural networks and deep learning [6]. Preliminary declaration of the number of groups. A lower value of β yields better results, but more iterations are required to get there [7]. Since it can only identify one threshold value, it could not function effectively with photos that feature histograms with more than two peaks [8]. The high dimensionality of the matrix and the high correlation of the Haralick characteristics are two disadvantages of the GLCM technique [9].

III. Proposed Methodology

An aberrant brain cell development is called a brain tumor. Better detail on the different soft tissues in the human body can be seen in MRI. Compared to CT, ultrasound, and X-ray, MRI images yield superior findings. Hence, the brain tumor type prediction model based on MRI is designed using the FANET and GLRLM with an ensemble classifier. Figure 1 displays the flowchart used to identify different forms of brain cancer using brain MRI.

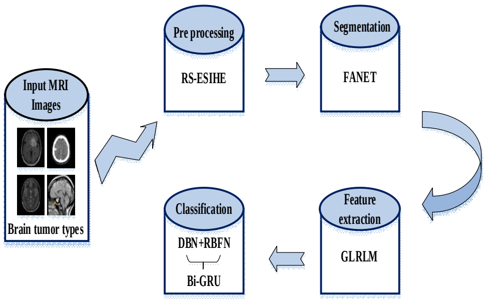


Figure 1. Process flow of the proposed model for detecting types of brain tumor

In this proposed model, the brain tumor MRI are collected and pre-processed using RS-ESIHE for improving the resolution of the gathered input images. The pre-processed images are segmented using the FANET segmentation that combines the feature mapping from the current training epoch with the previous epoch mask. The learnt feature mappings at various convolutional layers are then given hard attention using the previous epoch mask. The segmented images are extracted using the GLRLM technique to train the ensemble learning classifier for predicting the types of brain tumor.

A. RS-ESIHE

The histogram is theoretically decomposed in a similar way by the recursive version of ESIHE, or RS-ESIHE [10]. RS-ESIHE recursively breaks down the data to create 2^{v} sub-histograms by using the exposure thresholds of specific sub-histograms around recursion level v. Following deconstruction, each deconstructed subhistogram is subjected to individual equalization. For reasons of simplicity, recursion level v is taken to be two. The subdividing, equalization, brightness threshold, and histogram clipping are all computed using the RS-ESIHE approach. The FANET segmentation process uses the improved output image from RS-ESIHE as input to identify the precise brain region where the tumor is located.

B. Fanet segmentation

An encoder-decoder arrangement is used in several segmentation schemes [11]. To create a system that encourages the transmission of data from the learning paradigms of the present and previous epochs while also facilitating attentiveness, combine SE-residual and Mix Pool blocks. The encoder builds a compact representation of the input image after gradually down-sampling it. After that, the decoder rebuilds the semantic representation using this compact representation that has been progressively up-sampled and mixed with encoder features. The SE-residual block is used to build both the encoder and the decoder. For each resolution scale, an extra concatenation of the encoder's initial resolution representation of the feature is added.

C. GLRLM

GLRLM is a feature extractor method that primarily extracts an image texture feature [12]. Run length non-uniformity, grey level non-uniformity, run percentage, low and high grey level run emphasizing, short and long runs with low and high grey level emphasizing, and long runs with low and high grey level emphasizing. According to their appearance and historical development, all of the qualities listed above are without a doubt in the same category. Therefore, in suggested model, these 11 features are extracted using the GLRLM equations that are presented above.

D. Ensemble learning

1. Deep Belief Network (DBN)

A probabilistic multi-layer neural network referred to as a Deep Belief Network (DBN) that makes use of several Restricted Boltzmann Machines (RBMs). The DBN model architectural diagram, which has two RBMs, is shown in Fig. 4. Supervised fine-tuning and unsupervised pre-training are two components of the DBN training process [13]. By stacking on the procedure, a large number of RBMs are successively trained with the unsupervised pattern in order to create a DBN model. A higher-level RBM uses an output from a lower-level RBM as its input. After all RBMs are trained, a second supervised network layer is added to the top layer.

2. Radial basis function network

One kind of RBFN is receptive-field neural networks for function approximation. The three layers that comprise the feed-forward structure of the RBFN are the input layer, hidden layer, and output layer. The input layer connects the 14 landslide-related variables that make up the dataset's inputs. The output layer makes predictions about the likelihood of landslides. A specifically created radial basis function, the Gaussian function is commonly employed to describe the activation function for the buried layer [14]. One advantage of the RBFN is its ability to learn and resolve the nonlinearity issue fast in high-dimensional space by the use of several linear radial basis function combinations. Thus, it has been effectively used to address a variety of challenging environmental issues, such as modelling the sensitivity to landslides and floods.

3. Bidirectional gate recurrent unit

BiGRU specifically incorporates gates that prevent information loss [15]. By creating an update gate by merging the LSTM's forget and output gates, it simplifies the BiGRU architecture and dramatically reduces disk usage. By producing output in both forward and backward directions, the BiGRU model efficiently draws attention to important information found in a text. The GRU model may be more adept at processing lengthy texts since it automatically determines during training which resources are necessary and which can be dropped. However, due to the fact that a single-way GRU network's states never change from front to rear, it may overlook crucial information in text sentiment analysis. Empirical data clearly indicates that BiGRU performs better than GRU. In this proposed methodology, the deep learning algorithm with the DBN and RBFN are stacked and given to the classifier such as BiGRU algorithm (DBFN-BiGRU) to predict brain tumor detection.

IV. Result And Discussion

Detection of brain tumor types based on FANET segmentation and GLRLM with Ensemble learning is designed and implemented. The NVIDIA GeForce RTX 3070 GPU, which has 64GB (RAM) and Intel Core i7 processor are the system CPU combinations used by the MATLAB software. In this proposed model, initially MRI of brain tumor are gathered and contrast enhanced by using the RS-ESIHE method. Then, the FANET segmentation is performed to segment the tumor region and are extracted for features using the GLRLM technique. The brain tumor types are trained and classified using Ensemble learning.

A. Dataset Description

Different types of MRI-based brain tumors are included in this dataset, which is utilized as an input dataset for this framework [16]. This dataset contained 2075 data that the classifier used to create its best predictions of brain tumors involved 4 various kinds namely gliomas, pituitary, meningiomas, and no tumors. In this case, 80% (1660) is employed for training and 20% (415) for testing.

Figure 2 demonstrates the transformation of MRI images utilizing RS-ESIHE for image enhancement and FANET for segmentation. The first row of the image in Figure 2 illustrates the original image, the 2nd row represents the enhanced image by the RS-ESIHE approach, and the last row provides the tumor-segmented images based on ensemble learning.

The proposed model confusion metrics are shown in Figure 3 (a). A confusion matrix provides a table arrangement for various projected outcomes and supports visualising them. It creates a table with all of a classifier's predicted and actual values. The Receiver Operating Characteristic Curve (ROC) for the brain tumors prediction of MRI images is shown in Figure 3 (b). An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. For evaluating the model, the performance parameters which are Accuracy, Precision, Specificity, False Positive Rate (FPR), False Negative Rate (FNR), Negative Predictive Value (NPV), F1-Score, Error Matthew's correlation coefficient (MCC) and Kappa are evaluated and compared with the existing model such as Deep-Convolutional Neural Network (DCNN), SENET (Squeeze-and-Excitation Network) and Mask R-CNN (Region Convolutional Neural Network).

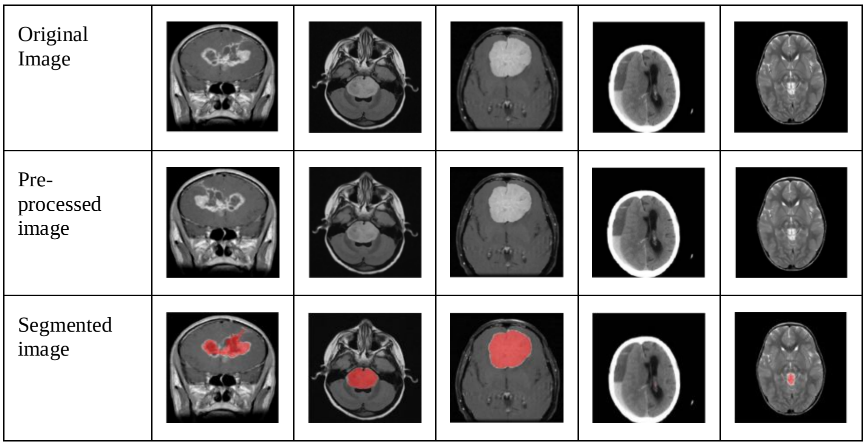
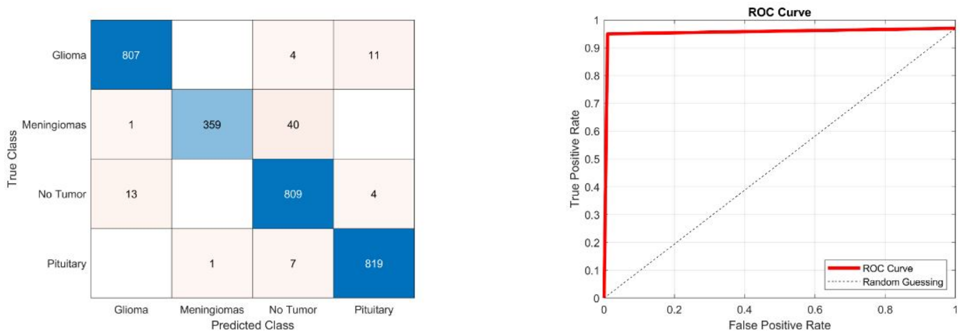


Figure 2. MRI image transformation using pre-processing and segmentation methods



(a) (b)

Figure 3 (a) and (b) Confusion matrix and ROC plot for the proposed model

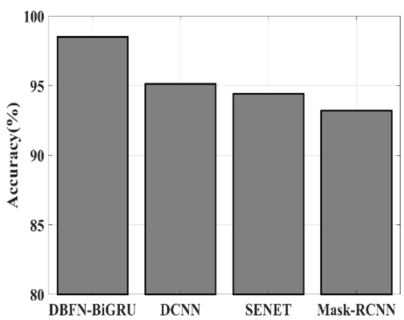


Figure 4. Accuracy comparison of existing models and DBFN-BiGRU proposed model

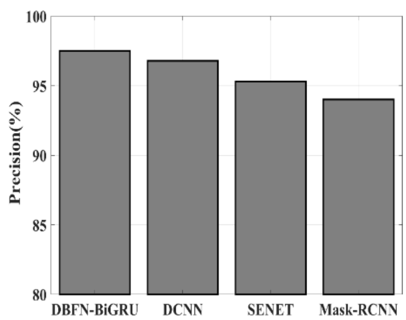


Figure 5. Precision examination of existing techniques and DBFN-BiGRU proposed model

Figure 4 exemplifies the performance measurement of accuracy between DBFN-BiGRU and existing techniques. The DBFN-BiGRU is compared with existing methods including DCNN, SENET and Mask-RCNN. The achieved accuracy for the DBFN-BiGRU and the existing methods are 98.5%, 95.13%, 94.42% and 93.2%. The DBFN-BiGRU model is more precise when compared to the existing approaches. Figure 5 depicts a comparison of Precision between the DBFN-BiGRU and the existing methods. The attained Precision for the DBFN-BiGRU and existing techniques. The DBFN-BiGRU is compared with existing methods including DCNN, SENET and Mask-RCNN. The achieved precision for the DBFN-BiGRU and the existing methods are 97.5%, 96.79%, 95.31% and 94.01%. Consequently, the DBFN-BiGRU model is superior to existing methodologies.

Figure 6 compares the DBFN-BiGRU with existing approaches in terms of specificity. The DBFN-BiGRU model is compared to existing techniques including DCNN, SENET and Mask-RCNN approaches. The DBFN-BiGRU and the existing model respective specificity values are 99.0%, 96.54%, 92.61% and 91.24%. Figure 7 compares the DBFN-BiGRU with the existing model's negative predictive value (NPV) data. The DBFN-BiGRU and existing models like the DCNN, SENET and Mask-RCNN have achieved NPVs of 99.10%, 97.13%, 95.14% and 94.43% respectively. As a result, the DBFN-BiGRU’s NPV value is higher than the existing model's.

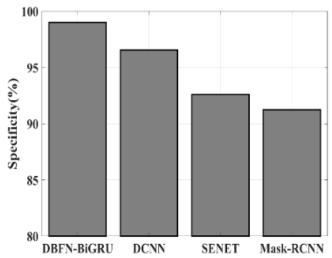


Figure 6. Specificity comparison of existing techniques and DBFN-BiGRU proposed model

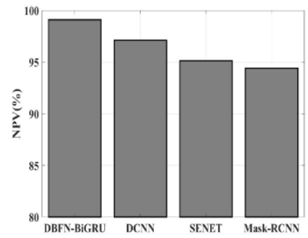


Figure 7. NPV comparison of existing techniques and DBFN-BiGRU proposed model

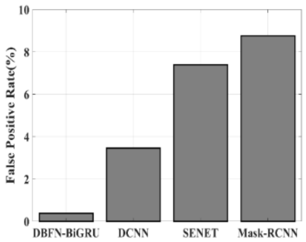


Figure 8. FPR comparison of existing techniques and DBFN-BiGRU proposed model

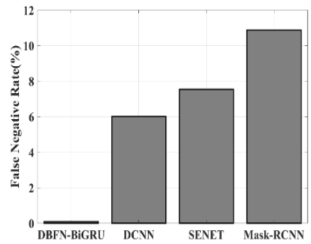


Figure 9. FNR comparison of existing techniques and DBFN-BiGRU proposed model

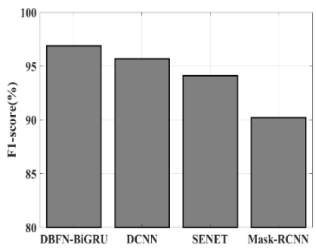


Figure 10. F1-Score comparison of existing techniques and DBFN-BiGRU proposed model

A comparison between the DBFN-BiGRU and existing techniques is shown in Figures 8 and 9. A false positive occurs when the model forecasts the positive class inaccurately. When the model predicts the negative class erroneously, the consequence is a false negative. For the DCNN, SENET and Mask-RCNN, the FPR and FNR rates attained are 0.37%, 3.46%, 7.39% and 8.76% and 0.098%, 6.02%, 7.54% and 10.88% respectively. The model performs better than the existing model based on the obtained FPR and FNR values. F1_score Evaluation of the DBFN-BiGRU and existing model are illustrated in Figure 10. The attained F1_score values for DBFN-BiGRU, DCNN, SENET and Mask-RCNN are 96.89%, 95.67%, 94.11% and 90.21%. This results that the specificity and F1_score value of the DBFN-BiGRU is greater than the existing model. Thus, the proposed model DBFN-BiGRU attain better performance metrics than the existing model.

V. CONCLUSION

Implementation of the DBFN-BiGRU proposed ensemble learning-based brain tumor type classification was designed and evaluated with existing brain tumor detection models. One of the best imaging process available for diagnosing brain tumors right now is magnetic resonance imaging or MRI. The computer-aided process for brain tumor detection lacks with the standard MRI due to the unwanted regions in the brain MRI. In this designed model, collected MRI images are pre-processed and segmented using RS-ESIHE and FANET. The GLRLM approach is used to extract the segmented image features and the ensemble classifier is used to predict the type of brain tumor. Performance metrics such as Accuracy, precision, F1-Score, error and specificity are attained for this designed model. The attained performance metrics values for the proposed model are 98.5%, 97.5%, 96.8% 1.5% and 99%. Comparisons are made between the evaluated values and existing approaches, such as DCNN, SENET and Mask-RCNN. Detection of brain tumor types based on FANET segmentation and GLRLM with Ensemble learning is better than the existing model. In future, the real-time processing of MRI based on this proposed model can be designed for many healthcare applications such as brain tumor detection, kidney disease prediction, retinal disease prediction etc., with the standard dataset.

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