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Brain Tumor Image Processing Using Fine-Tuned Resnet-101 Classification Model

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Abstract

Medical image processing relies heavily on the diagnosis of brain tumor images. It aids doctors in determining the correct diagnosis and management. One of the primary imaging methods for studying brain tissue is MR imaging. In recent years, deep learning techniques have shown significant potential in image processing. However, the modest quantity of medical images is a restriction of the classification of medical images. As a result of this restriction, fewer medical photos are available. Fine-tuned ResNet-101 (FR-101) is proposed to classify the brain tumor images to counteract this issue. Weiner filter is used to de-noise the acquired raw MR images, and the adaptive histogram equalization technique is used to improve contrast. A stacked autoencoder is utilized in the segmentation procedure to separate the tumor from healthy brain parts from the preprocessed data. The marker-based watershed technique is used to identify the tumor location and structure in the segmented data. The recommended approach is then used in the classification stage. To obtain the highest level of accuracy for our research, accuracy, precision, f1-score, recall, and mean absolute error are the measures of success are studied as well as a comparison of the suggested approach with a few other existing methods.

Keywords- *Medical Image Processing, Brain Tumor, MRI, Deep Learning, Fine-tuned Resnet-101 (FR-101)*

I. INTRODUCTION

To identify images into determined categories and isolate the region of interest (ROI), two of the most popular image processing methods are image segmentation and classification. To process images, extract characteristics from them, and analyze and interpret them, Image segmentation and classification are crucial processes in a broad range of applications. This method has several uses in neuro-imaging, including "tissue categorization, tumor localization, tumor volume calculation, blood cell outlining, surgical planning, and patient matching". Both the "MRI and CT image" are used to remove the abnormal tissue and analyze its form, size, and location in the brain. A brain tumor is an uncontrolled, oncogenic, and malignant cell growth. Brain tumors, sometimes called lesions or neoplasia, may be divided into two main types: Primary and Metastatic. Malignant tumor cancers begin in brain tissue and its immediate surroundings [1]. The medical images obtained using the previous approaches are consulted in the process of brain tumor diagnosis. There is a wide variety of software and application accessible to lessen the amount of work done by humans. The primary goals of brain tumor detection are to identify whether or not a tumor is present and to determine the extent to which cancer has spread within the region that is being examined [2]. Because of its high-quality spatial images and better contrast values for soft tissue structures, MRI has emerged as a prominent noninvasive method for brain imaging, even if deep learning is the standard method for detecting brain cancer. Recent research has demonstrated the use of medical imaging for diagnosis, therapy, and outcome evaluation. Tumor identification based on medical imaging is often accomplished via the use of computer tools known as classification, which categorizes images as either benign or malignant. Image classification tasks are also being used to quantify tumors in diagnostic imaging studies. Tumor categorization is still a challenge for future image processing research groups since several aspects of tumor cells, such as the size, contrasts, as well as morphology around the tumor cell, exhibit similar patterns [3]. There are many different kinds of tumors, but malignant tumors and their structures are particularly dangerous if they are not identified at an early stage. Sometimes these tumors have very low contrast and are hazy, making it difficult to segment them. Additionally, they may spread to various parts of the brain and can be any size or form. Segmenting them can be quite

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challenging because of the functional challenge present in the brain tumor. It has become more difficult to recognize and diagnose ailments from medical pictures due to the complexity. Additionally, as seen by the image supplied, the region is severely infected. Hence, we proposed the Fine-tuned ResNet-101 (FR-101) for brain tumor classification.

Contributions to the paper

- Weiner filter is used to de-noise the acquired raw MR images for image preprocessing.
- The adaptive histogram equalization method is used for contrast enhancement.
- Using a stacked autoencoder, we can separate tumors from background tissue in an MRI scan of the brain.
- Marker-based watershed is used to process of transforming data into numerical features.
- The proposed FR-101 is used to classify brain tumors.

The remainder of this paper is structured as follows: A related work is included in Part II. The suggested technique is presented in Part III. Part IV contains the results and discussion. The conclusion is in Part V.

II. RELATED WORK

This paper reviews several research papers and technical reports authored by diverse writers. The research [4] used CNN to quickly and accurately categorize the three main kinds of brain tumors. The performance of traditional methods, ranged from 71.39-94.68%, with pre-processing based on regions. Evidence from MRI of the brain indicates a decline in the accuracy of contoured classification. The research [5] developed the CNN model for identifying brain malignancies. The method may be broken down into two important stages. Study [6] used an online digital library of MRI images of the brain to train "Machine Learning" for feature selection, and apply the "Support Vector Machine (SVM)" classifier to identify the kind of tumor present in new images. The research [7] proposed a model that we name the enhanced classification model for brain tumor diagnosis. The method is used to estimate the correct categorization of tumor pictures based on input MRI images. Research [8] suggested a method for improving images of brain tumors by combining the "ICA-LDA (independent component analysis-linear discriminate analysis algorithm) model with the ARHE (adaptive area based histogram enhancement)" technology. The method of image fusion may be used for combining two or more input images. Convolutional neural networks were used to build the study's [9] proposed deep learning technique. Thus, a complex CNN model is created, cross-validated trained and evaluated on brain MRI images taken from public databases. The research [10] was created to be used for tumor assessment. Next, the brain tumor is cut out utilizing the most cutting-edge methods possible. To begin the segmentation procedure, the MRI image must first undergo preprocessing. In the next step, features are extracted from the photos that have already been preprocessed. A modified variation of the "Gabor wavelet transform" called the "improved Gabor wavelet transform (IGWT)" is used in the feature extraction method.

III. PROPOSED METHODOLOGY

In this paper, we proposed to fine-tune ResNet-101 (FR-101) for the brain tumor images. The phrase "image processing" refers to a collection of techniques that may be used on a picture to enhance it or get valuable information from it. This type of denoising uses an image as the input and may produce the same image or a subset of its properties as the output. Figure 1 shows the schematic representation of the proposed methodology.

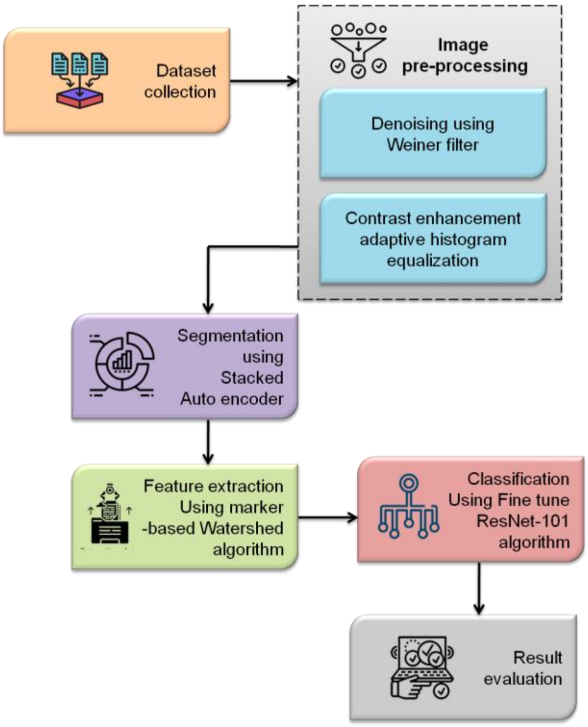

Figure 1: Schematic representation of a proposed method

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A. Data collection

Brain MRI image datasets were collected from BraTS MRI images. There are 280 images of the brain in this collection. 130 images are collected from this for the training process, of which 70 are determined to be normal and 60 to be abnormal. A total of 150 images are used in the testing procedure, with 30 being deemed normal and 120 being deemed abnormal. Figure 2 depicts the dataset sample.

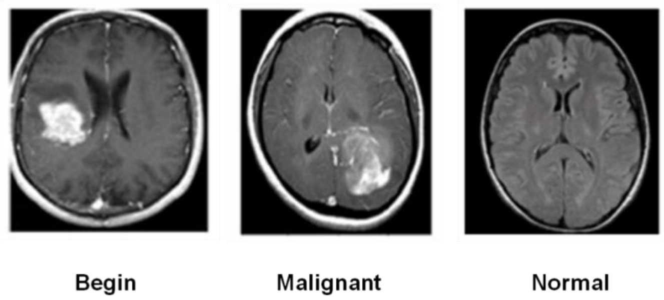

Figure 2: Dataset sample

B. Image pre-processing

This process on images at the lowest level of analysis known as image pre-processing attempt to enhance the image data by suppressing unnecessary deformities or enhancing certain crucial image features. The image pre-processing is performed the denoising using Weiner filter and Contrast enhancement using adaptive histogram equalization.

a. Denoising using Weiner filter

The numerical solution of the Weiner filter removes the contaminated images. Since the blurred picture is retrieved using converse filtering, it retains the perfect trade-off between converse filtering and signal loss reduction. By assuming that the images and disturbance are linear arbitrary processes with known imaginary properties, the filter is a good approximation. This filter's operation is described by,

$$C(f,s) = \frac{K^*(f,s)\eta_T(f,s)}{|B(f,s)|^2\eta_T(f,s)+\eta_D(f,s)} \quad (1)$$

Where $\eta_T(f,s)$ and $\eta_D(f,s)$ are the frequency levels of the image and noise, respectively; $B(f,s)$ is the softening filter.

b. Contrast enhancement using adaptive histogram equalization

"Adaptive histogram equalization (AHE)" is adjusted by contrast constrained adaptive equalization. This technique applies an enhancement function to all nearby pixels and derives a transformation function. The contrast-enhanced of this sets it apart from AHE. The AHE technique, which is utilized for the enhancement procedure, uses a maximum value to trim the histogram and redistribute the greyscale picture. Separate algorithms are used for the backdrop and the ground to reduce noise and improve contrast. Distribution parameters are used to determine the form of the histogram equalization graph and the bell-shaped histogram. Grayscale and colorful images are both covered by AHE. Use the "clip limit" function to add a limit to a noisy image.

Algorithm AHE

Step 1: acquisition of an MRI image.

Step 2: Gather all of the input data that will be utilized in the improvement process, such as the number of regions in each row and column, the dynamic range, the clip limit, and the distribution variable category.

Step 3: Separate the original image into an area and prepare the data for the inputs.

Step 4: The process is used on the tile.

Step 5: Create a clipped histogram and grey level image identification. Since there are equal quantities of pixels in each grey level in the contextual area, the average image in each level is expressed in the form.

Step 6: Preprocessing techniques images by approximating source image identification. Using four image clusters, the identification process is performed, and each scanning layer completely overlaps in the image area before a single image is extracted and the four identification processes are done to that image. Repeat over an image, interpolating between those results to achieve improved images.

C. Segmentation using stacked auto-encoder

An uncontrolled Item is the "Back Propagation (BP)" training method for stacked auto-encoder networks. The encoder and decoder are the two halves of the system. To extract the characteristics from the input data, an encoder turns it into a hidden representation. The decoder returns the input to the hidden image. The difference in inaccuracy between the original input and the reconstructed input is used to increase the values' accuracy. To accurately depict the input, weights are adjusted depending on the difference

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in inaccuracy between the original and reconstructed inputs. An auto-encoder is shown in Figure 3.

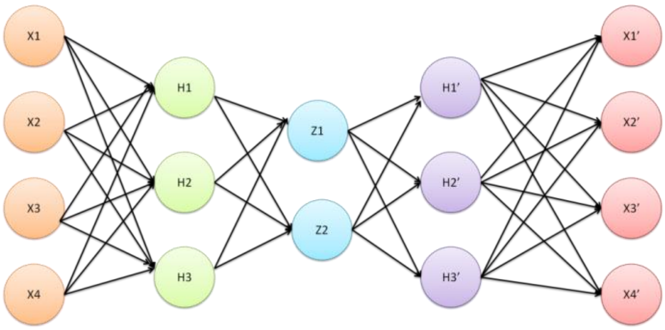

Figure 3: Structure of Autoencoder

The Stacked Auto-encoder network consists of one or many autoencoders and a "SoftMax layer". The Stacked Auto-encoder network is shown in Figure 4.

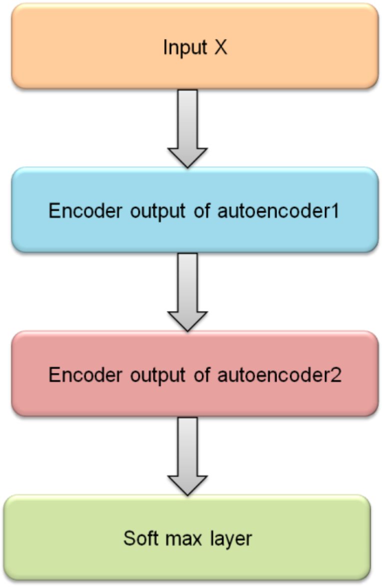

Figure 4: Stacked Auto-encoder

The following are the steps for training the Stacked Auto-encoder network:

- ➢ The first autoencoder should be trained to minimize the difference between the initial input and the reconstructed output.
- ➢ Training the second utilizing the hidden autoencoder layer output as input.
- ➢ For more Auto encoders, repeat the process.
- ➢ To train a SoftMax layer, use the labeled data as an input for the last hidden layer of the autoencoder, then use the supervised BP technique.
- ➢ To good the parameters and biased, run the network via supervised BP training.

D. Feature extraction using marker-based watershed algorithm

The technique of turning the raw range of input features that may be processed while keeping the details of the original data set is known as feature extraction. Watershed is a mathematical morphology-based image segmentation approach. It can get accurate, one-pixel-wide boundaries. The watershed method considers the image a geographical surface, with grey values representing elevation from the ground. The described marker-based watershed algorithm performs in stages. Obtaining and converting the target image to a grayscale image is the initial stage in the segmentation process. The input image is used to define a structure or probe element. To calculate the “foreground and background markers”, the watershed algorithm may now be seen in action. The image grouping method is one of the most effective. The image is converted to a greyscale image to execute the watershed. Pixels with greater gradient magnitudes are kept, while lower values are removed, using the reconstruction operator. Over-segmentation has been eliminated by the use of color in the image, but the noise remains. When the color image is opened and closed using the Threshold opening and closing function, the image may be reconstructed using marker segmentation. Over-segmentation may be reduced using the marker-based approach, which selects the local minima from the color of the image to do so using the marker-based segmentation approach; an image may be segmented to remove a tumor from it with closed edges.

E. Classification using fine-tuned ResNet 101 algorithm

ResNet-101 is an improved version of ResNet (first developed at Google) with 101 layers. ResNet-101, the pre-trained model, was further improved by fine-tuning modifying resource allocation and avoiding memory exhaustion. ResNet 101, short for Residual Networks, is the structure we used for the classification challenge, and it has significant relevance to issues in computer vision. To prevent gradients from regressing to zero after chain rule applications, a ResNet network makes advantage of direct gradient-flowing residual connections. ResNet-101 is the total number of convolutional layers. In addition, there are a total of 33 layer blocks, and the output from the preceding layer is utilized as input by the layer after it through a summing operator, with the first operand being the residual

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connections described above. Each of the remaining 4 blocks uses the output of the previous block as input to a "convolution layer with a filter size of 1x1 and a stride of 1", and then passes the result through a batch normalization layer that carries out a normalization operation, and passes the results to the summing algorithm at the block's output last. Table1 demonstrates the variations in dense block depths.

Table 1: RESNET 101

Layer Name	Output Size	101 Layer
Conv1	112*112	7*7,64, stride 2
Conv2	56*56	3*3 max pool, stride 2 1*1.64 1.3*3.64 1*3 1*1.256
Conv3	28*28	1*1.128 [3*3,128]*4 1*1.512
Conv4	14*14	1*1.256 [3*3,256]*23 1*1,1024
Conv5	7*7	1*1,512 [3*3.512]*3 1*1,2048
	1*1	Average pool,1000-Dfc Softmax
FLOPs	7.6*10^9	

IV. RESULT AND DISCUSSION

In this paper, we proposed the fine-tuned ResNet-101 [FR-101] for classifying brain tumors. Accuracy, precision, f1-score, recall, and MAE were analyzed with proposed and existing methods. Existing approaches such as Deep Neural Network [DNN], Conventional Neural Network [CNN], Conventional Neural Network with Support Vector Machine [SVM], and Long Short Term Memory [LSTM] are compared with the proposed method.

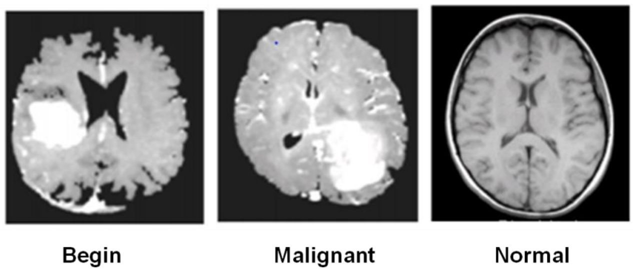

Figure 5: Output of pre-processed images

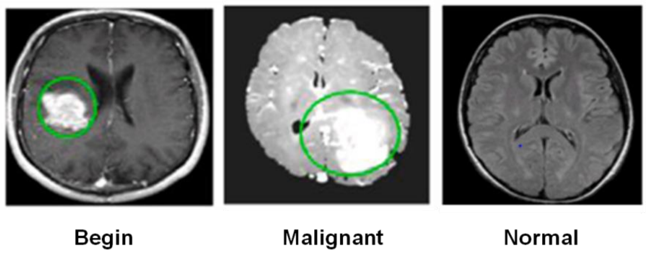

Figure 6: Output of feature extracted images

Figure 5 and 6 demonstrates the outcome of automated brain tumor identification and classification utilizing MRI brain images. Effective brain tumor categorization of MRI images plays an important part in medical assessment as well as the decision-making process for the treatment of patients. The FR-101 technique is suggested in the research as a method for improved brain tumor detection and classification.

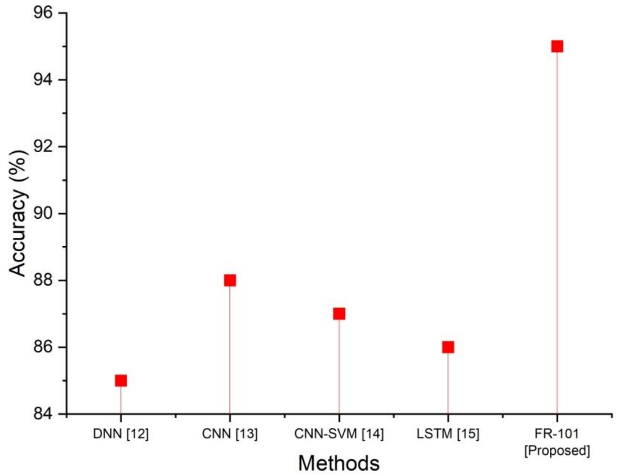

Figure 7: Comparison of the accuracy

The accuracy comparison is shown in Figure 7. "Accuracy" is a measurement's conformance to a value or standard. To measure accurately, you require precision. Accurate measurements aren't required for precision. Because measured values may be sorted.

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$$\text{Accuracy} = \frac{(A + B)}{(A + B + D + C)} \quad (2)$$

Where,

A=True Negative

B=True Positive

C=False Positive

D=False Negative

The suggested work [FR-101] was found to be more accurate (95%) than the existing methods like DNN (85%), CNN (88%), CNN-SVM (87%), and LSTM (86%).

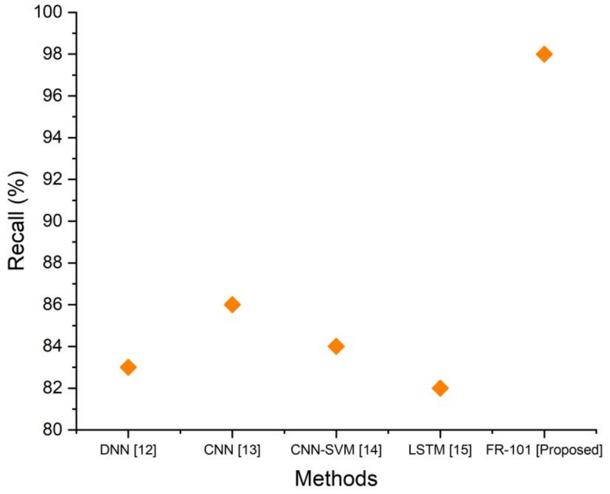

Figure 8: Comparison of the recall

Figure 8 comparison of the recall. For information systems that deal with medical images, recall measures how well technology can track down the backing data that a user has requested be provided to them. A collection of measures in the following form has been identified as necessary:

$$\text{Recall} = \frac{\mathit{True\ positive}}{\mathit{total\ number\ of\ actual\ positives}} \quad (3)$$

The suggested work [FR-101] was found to be MRI scan technology can track down the backing data and has more recall (98%) than the existing methods like DNN (83%), CNN (86%), CNN-SVM (84%), and LSTM (82%).

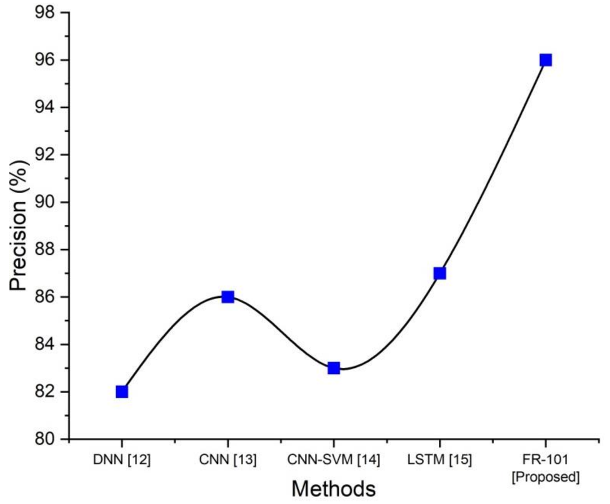

Figure 9: Comparison of the precision

Figure 9 depicts the comparison of the precision. Precision may also be quantified using a metric known as "positive predictive value" (PPV). A measure of precision counts the number of accurate class predictions made from a given sample. In other words, it's a comparison of actual results to predicted results. Following is a formula that may be used to determine the precision of a given measurement:

$$\text{Precision} = \frac{\text{True positive}}{\text{Total predicted positive}} \quad (4)$$

The proposed method FR-101 shows predictions out of a given sample data has more significance (96%) precision than the other existing methods like DNN (82%), CNN (86%), CNN-SVM (83%), and LSTM (87%).

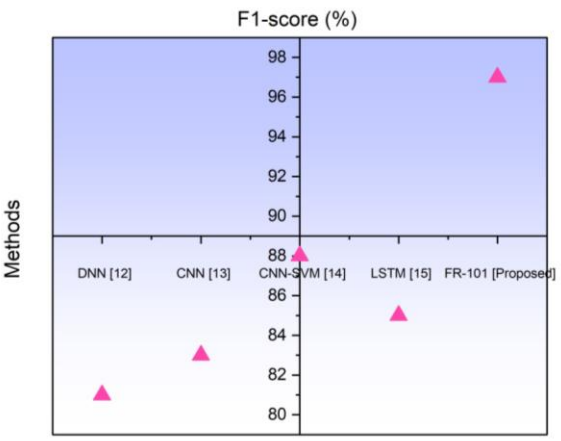

Figure 10: Comparison of the F1-score

Figure 10 depicts the comparison of the F1 score. Precision and recall are both taken into consideration by the F1-Score.

The term "frequency mean" is used to describe the median of two distributions; thus, the average of the two. The harmonic mean is an alternative method for averaging data, and it is frequently claimed that it is more suited for ratios (such as precision and recall) than the normal statistical distribution. Throughout this investigation, the proposed FR-101 has more f1-score (97%) than the existing methods like DNN (81%), CNN (83%), CNN-SVM (87%), and LSTM (85%).

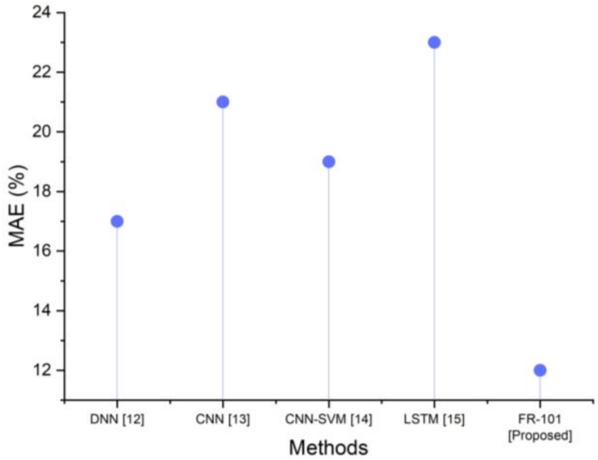

Figure 11: Mean absolute error of the proposed and existing methods

Figure 11 depicts the mean absolute error. The MAE of a technique is the average of the individual prediction errors for each instance in the validation set, as measured against the test data set. A lower number for the metrics typically implies improved image quality. An additional indicator that might help flesh out the evaluation of efficiency is a visual assessment of the forecast error.

$$MAE = \frac{\sum_{j=1}^{k}|x_j - z_j|}{k} \quad (5)$$

Where,

x_j= prediction

z_j= true value

k= total number of data points

The suggested approach FR-101 has a minimal mean absolute error (12%) than the existing methods like DNN (17%), CNN (21%), CNN-SVM (19%), and LSTM (23%).

The suggested model is turned on in MATLAB/Simulink, and its effectiveness is then compared to other models, such as [DNN, CNN, CNN-SVM, and LSTM]. Current methods have the following drawbacks. One of the drawbacks of the deep neural network is that the structure of the system cannot be reused to analyze a limited number of images [12]. Large training data are required; object location and orientation should not be encoded. CNN model has been modeled to solve the image classification issue [13]. When there is more noise in the data, i.e. the target classes overlap, the algorithm performs poorly. If there are more components per data point than there are training data samples, both the CNN and the SVM will lose poorly. [14]. The size of the input image is fixed and cannot be increased owing to memory constraints, which is one of the 3D drawbacks network [15]. As a result, we accomplish the suggested analysis of the FR-101 for brain tumor classification.

V. CONCLUSION

In this paper, we proposed fine-tuned ResNet 101 for a brain tumor. The research analyzed 280 MRI images from the BraTS database. Raw MR images are de-noised using a Weiner filter, and contrast is enhanced with adaptive histogram equalization. The segmentation approach uses a stacked auto-encoder to identify between tumorous and nontumor genic regions of the brain in the raw data. Tumor location and structure in the segmented data are identified using a marker-based watershed method. Accuracy, recall, precision, F1-score, and mean absolute error (MAE) were all measured and analyzed in the experiments. Accuracy (95%), recall (98%), precision (96%), F1 score (97%), and MAE (12%) is all provided as results of the research. The recommended strategy is more effective than the current approaches. The efficiency of this research can be improved by analyzing additional data in the future. It must be tested on larger datasets including individuals with a wide range of capabilities and backgrounds to increase its flexibility and employ it in future medical image processing.

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