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Brain Tumor Classification Utilizing Deep Learning with Long Short-Term Memory Techniques via Magnetic Resonance Images

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Abstract: Detection of the brain tumor is a major challenge in the field of medical imaging. Manually recognizing brain tumors constitutes a costly and arduous process for radiologists; hence it is necessary to implement a computerized technique. However, even experienced medical radiologists face difficulties in accurately and reliably analyzing MRI (Magnetic Resonance Imaging) images to diagnose brain tumors**.** Because precision matters most for classification, computer vision scientists have established a variety of techniques, however they still have trouble with low fidelity. The suggested technique can be separated into two distinct steps: preprocessing and classification. Initially, the data are pre-processed via two main steps: image enhancement, noise removal, and data augmentation. Next, images that have been processed are loaded to the ResNet50 model for extraction of features. Secondly, all of the extracted features are trained and categorized into four classes using a LSTM ***(Long short term memory)*** multilayer with dropout between its layers. The experiment's results exhibits that the proposed technique scored an accuracy of 99.26%.

Keywords: Convolutional Neural Network (CNN); Deep Learning (DL); Long Short Term Memory (LSTM), Magnetic Image Resonance (MRI).

1. Introduction

Cancer is among of the top reasons of mortality globally and poses a substantial obstacle in boosting the lifespan. A tumor in brain develops when abnormal cells grow inside the brain, causing harm to specific tissues and leading to cancer [1]. The American Cancer Society (ASC) estimates that by 2023, 24, 810 persons would develop malignant tumors, resulting in 18, 990 deaths. There are approximately 150 different types of brain tumors in people. There are both benign as well as malignant tumors amongst them (Pradhan et al., 2021). The World Health Organization (WHO) classifies brain tumors as four classes. Class 1 and 2 tumors are milder (e.g., meningiomas), whereas class 3 and 4 tumors are far more serious (e.g., glioma). Regarding healthcare, annual prevalence of meningioma, pituitary, and glioma classes range from 15%, 15%, and 45%, as well [2]. Benign tumors as harmless tumors which originate inside the brain then spread towards surrounding cell and tissue structures. This kind of tumor is considered less aggressive because it is incapable of spreading to other parts of the organism. Abnormal cell growth can interfere with easily separated areas of the brain [3]. Malignant tumors, in contrast, as malignancies which expand quickly outside clear borders, penetrate adjacent tumor cells, and impact various parts within the body.

Brain tumors are diagnosed through a series of physical and neurological examinations. Clinicians manage tumors using a variety of methods, including radiotherapy, surgery, and chemotherapy, according to the tumor's category, forms, and size. The most effective imaging method is magnetic resonance imaging (MRI), which is a unique harmless and non-ionizing imaging modality which provides informative data on the size, location, and shape of brain tumor in both 2D and 3D formats [4]. As a consequence, the stage and form of the cancer are exactly determined, and a plan for therapy developed. Because of the vast number of cases, manual image evaluation takes a long time, is physically demanding, and may be inaccurate. To deal with this issue, the establishment of an automated Computer-Aided Diagnosis (CAD) application is necessary to reduce the burden of the detection and categorization of MRI scans and provide tool for helping physicians and clinicians [5]. Additionally, MRI would assist in better understanding the characteristics of the neural tissue, such as relaxing periods, velocity of the flow, and changes in the chemical substances [6]. It is possible for improving physicians' recognizing skills by minimizing the amount of time required to conduct accurate evaluation via the utilization of completely computerized recognition and analysis [7].

Machine Learning (ML) and Artificial Intelligence (AI) gadgets are commonly utilized to detect fake conditions that humans are unable to recognize. Nevertheless, the spread of deception over worldwide is simple, however one cannot determine if the information transmitted is true or false. For examining actual data, ML and AI technique are applied in all fields. Brain tumor detection can be accomplished using ML and AI strategies, which each have its own set of features. During training, image features are derived exclusively from the original image [8]. The most effective methods for image processing right now are Convolutional Neural Networks (CNNs), which include several layers and outstanding accuracy in diagnosis if there are a large number of input images [9]. Surprisingly, different algorithms based on deep learning and ML was employed for tumors identifying (including lung tumors) and detects heart disease [10]. In addition, applying these tools clears ahead for precise and unaltered tumor recognition, allowing them to be recognized as distinguished among similar disorders. The key objective of the suggested method is to instinctively recognize the brain tumor from MRI images. To achieve this goal, an optimal combined classifier can be built using Long Short Term Memory (LSTM) and CNN structure. Following the classification procedure, the explanation associated with the suggested technique is evaluated.

The remainder of this paper is organized as follows:

Section. 2 displays a different studies of brain tumor classification techniques. Section. 3 describes the proposed model and its steps. Section. 4 explains the results. Finally, conclusion and future work are presented in section. 5.

2. Related Work

An improved technique for MRI brain tumor diagnosis that uses altered neural network has been proposed by Hemanth et al. [11]. 540 MRI scans were used to validate the proposed approach. Eight features were obtained employing GLCM and first-order histogram. Their approach scored satisfactory outcomes with an accuracy of 98%. In [12], the Gabor filter with the discrete wavelet transform (DWT) has been applied for deriving statistical characteristics for classification. In their method, the input was the segmented data of the tumor and a multi-layer perceptron (MLP) was utilized for the classification. Their approach obtained an accuracy of 91.9%. Medical technology and histopathological study of material from samples were mainly employed in order to brain tumors detection and categorization in [13]. A pathological examination, such as a CT or MRI, was usually utilized to determine the final evaluation. It is well understood as the major drawbacks associated with this clinical technique included it is intrusive, costly, and susceptible in collecting errors. Moreover, in [14] two main classification methods (fully connected neural network and CNN) were developed using an axial brain tumor image for training. The CNN architecture consisted of two convolutional layers along with two corresponding max-pooling layers, and two fully connected layers, with an optimal accuracy of 91.43%.

In [15] a hybrid ensemble technique for brain tumor identification using classic classifiers such random forest, K-nearest neighbor, and decision tree, based on the majority voting mechanism was suggested. Their method employed segmentation, feature extraction, and classification on 2556 images. Their strategy obtained overall accuracy of 97.3%. On the other hand, an exhaustive brain tumor categorization method has been offered in [16]. An auto encoder was employed to extract features from the axial perspective and used LSTM for classification. Their technique was evaluated on specified slices (989, axial only) and yielded the highest accuracy 92.13%. In [17] a CNN-based model for multi-class brain tumor classification using CNN was suggested. Their technique was adapted to an MRI data set that contained 3064 T1-CE MR images from 233 patients. The system is first trained to work as identifier in a GAN, which is generative adversarial network for basic features extraction. Various data augmentation operations were combined with GAN. It achieved accuracy values of 93.01% and 95.6% on the established and random splits, as well. In [18] an 18-weighted layered CNN-based CAD system for brain tumor classification has been proposed. Their approach was investigated on three datasets and yielded 94.74% accuracy for brain tumor-type classification and 90.35% for tumor assessing.

In [19] a comprehensive study comparing the performance of TL based CNN models pre-trained with VGG16, ResNet50, and InceptionV3 architectures for brain tumor cell prediction was performed. InceptionV3 carried an accuracy of 78%, while VGG16 had a high accuracy of 96% and ResNet50 had 95% accuracy. In [20] they deployed DL models to analyze MRI images, which is currently the most common and accurate method for early cancer diagnosis. A unique hybrid model (NADE) was developed by combining Neural Autoregressive Distribution Estimation (NADE) with the VGG16 structure. The designed system (VGG16-NADE) hybrid has high prediction accuracy (96.01%), precision 95.72%, and recall 95.64%, and F-measure 95.68%. A multi-classification system for MRI diagnoses between glioma, meningioma, pituitary, and normal was introduced in [21] put forward. The proposed multi-scale CNN model outperforms AlexNet and ResNet in terms of accuracy and efficiency, while requiring less computational resources. Their suggestion received of 91.2% and 91% for both accuracy an F1- score.

The primary contribution of the suggested method is stated as follows:

- A deep LSTM technique for brain tumor classification is provided that is less computationally intensive than high-cost DL models.
- Data augmentation improves classification accuracy on a small dataset, and the consequences of over fitting are investigated.
- The suggested technique is compared to current brain tumor classification approaches, and it outperforms the current approaches.

3. Materials and Methods

The present study's major steps include selecting a brain tumor dataset, pre-processing MRI images, extracting features, and classifying them using resolution. LSTM, dropout, and classification layer. Fig.2 describes a sample of each class in the used dataset. The computerized technique for recognizing and evaluating for brain tumors is being tested through collecting MRI images from Kaggle website. The used dataset contained 5712 MRI scans for training and 1311 MRI scans for testing. Table 1 indicates that this dataset includes four classes: pituitary, glioma, meningioma, and normal as shown within. This dataset's scans have three different viewpoints: axial, coronal, and sagittal. Fig.1 depicts the concept of the proposed method.

A. Data preparation and preprocessing:

In applications that are ongoing, MRI is impacted by fluctuations of the coil in the magnetic field, causing intensity in homogeneity and partial volume effect [22]. Image pre-processing enhances the visual quality of input images by reducing noise, increasing contrast, and removing low or high frequencies [23]. DL procedures use CNN for preprocessing and feature extraction. CNN has a layered organization. The images have been preprocessed for ease of use. First, data is gathered for enhancing the overall analysis results, and resized to 224 × 224 pixels. In order to guarantee uniform data distribution, image normalization was performed by dividing the images by the number of channels (255), resulting in normalized data within the range of [0, 1]. This improves convergence over neural network training. Image normalization was executed as shown in Equation (1):

$$X_{Norm} = \frac{X_{In} - X_{Min}}{X_{Max} - X_{Min}} \tag{1}$$

where, X_{Norm} represents the normalized data, X_{In} is input data, while X_{Max} and X_{Min} represent maximum and minimum values of the input data as well. Filtering is necessary for preprocessing. The median filter smoothed out images and eliminates noise through non-linear processing. The capacity it holds to mitigate noise and preserve edges has led to broad adoption. The median filter gradually replaces values in an image with their neighborhood median value as it relocates from pixel to pixel. By sorting the window's pixels mathematically and evaluating the central pixel with the median value, the median can be calculated. To improve model generalization, we used data augmentation, which adds variations to the dataset to reduce over fitting. Augmentation is performed on the validation dataset to validate the model with various inputs. The data augmentation technique uses the Keras Image Data Generator to perform various data augmentations. Many operations of data augmentation technique are applied on the images such as rotation range by 25%, width and height shifted by 30%, zoom range of 20%, and flipping vertically or horizontally. The final step involves data splitting to 80%, 10%, and 10% for training, test, and validation stages.

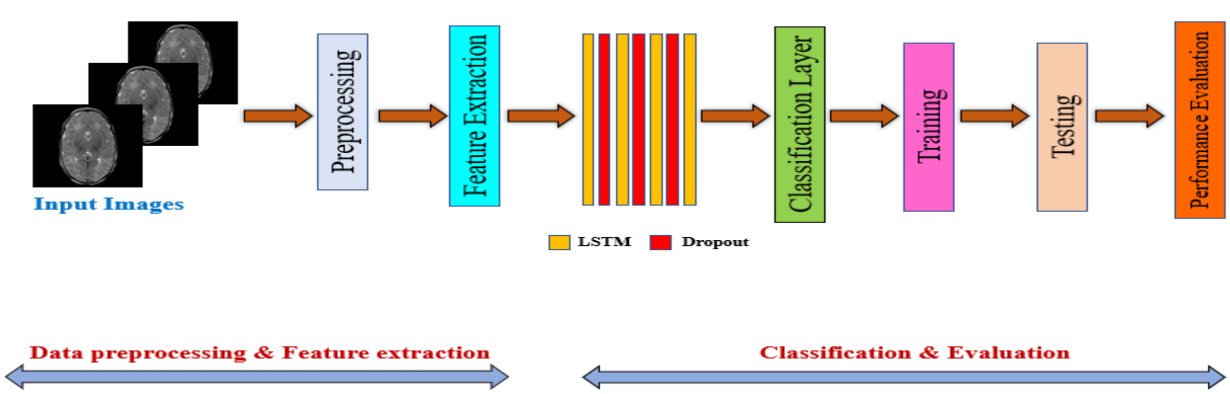


Fig. 1. Concept of the proposed model

B. Feature Extraction:

The model has two significant parts. The first is deep TL (ResNet50) for feature extraction while the additional part is classical CNN. ResNet, or residual neural network, acquired the ILSVRC in 2015. The feature was the existence of transmission connections that send the same data to deeper parts of a network. This data is then summed with the value estimated on missing layers and transmitted further. In the proposed system, ResNet50 is primarily used for feature extraction, while traditional classifier is utilized for training, validation, and testing. ResNet is a deep TL model that relies on residual learning. ResNet50 is a deep neural network with 50 layers. It begins with a convolution layer and ends by a fully connected layer, then includes 16 residual bottleneck blocks, each with three convolution layers [24].

Table 1:Dataset distribution

	Class	**No. of images in each class**
Train	Pituitary	1457
	Glioma	1321
	Meningioma	1339
	Normal	1595
	Total	5712
Test	Pituitary	300
	Glioma	300
	Meningioma	306
	Normal	405
	Total	1311

C. LSTM Concept:

CNN handles a network's input data autonomously. This strategy is appropriate for uncorrelated data however not for correlated data, like time series. The LSTM design has been recommended to address the long-term memory problem of RNNs [25]. Models of LSTM were created for addressing the long-term gradient vanishing challenges. LSTM uses memory cells connected by gates to control the flow of information. LSTM's selective storage and retrieval capabilities make it ideal for speech recognition, language translation, and video analysis. Using LSTM in medical image analysis shows promise for improving diagnosis and treatment planning for various health issues [26]. The proposed model includes an input layer, four LSTM layers, three dropout layers with a threshold of 0.1, and softmax layer. In LSTM layers, the first and second layers have 512, 256 neurons respectively, while the third and fourth layers have 128, 64 neurons as well. The four LSTM layers are constructed systematically to learn low- and high-grade feature representations for brain tumors. The classification layer is the final layer in which probabilities are computed using the softmax layer. The model generates the output based on the softmax according to Equation (2) [27]. We ran a variety of experiments to determine the model's best performance with the fewest losses.

$$S(M_i) = \frac{e^{M_i}}{\sum_{k=1}^{N} e^{M_k}} \quad (2)$$

The softmax layer receives input data from the previous layer (M_i) and has a total of N classes. Finally, the RMSprop optimizer was used to apply the categorical cross entropy loss function. The loss is calculated using the predicted class (or softmax output) and the class's ground truth probabilities, specified by Equation (3):

$$L_f = \sum_{m=1}^{C} y_m \,.\log y_m * \quad (3)$$

D. Classification Analysis of performance:

CNNs' outcomes can be evaluated using a variety of metrics, such as accuracy, precision, recall, F1-score, and confusion matrix. Accuracy is the metric that matters most for the results of our DL classifiers, as stated in Equation (4). It is basically the sum of true positives and true negatives divided by the total value of the confusion matrix components [28].

$$Ac = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \quad (4)$$

Precision, as indicated in Equation (5), means the overall number of positive results divided by the sum of true and false positives.

$$Pr = \frac{Tp}{Tp + Fp} \quad (5)$$

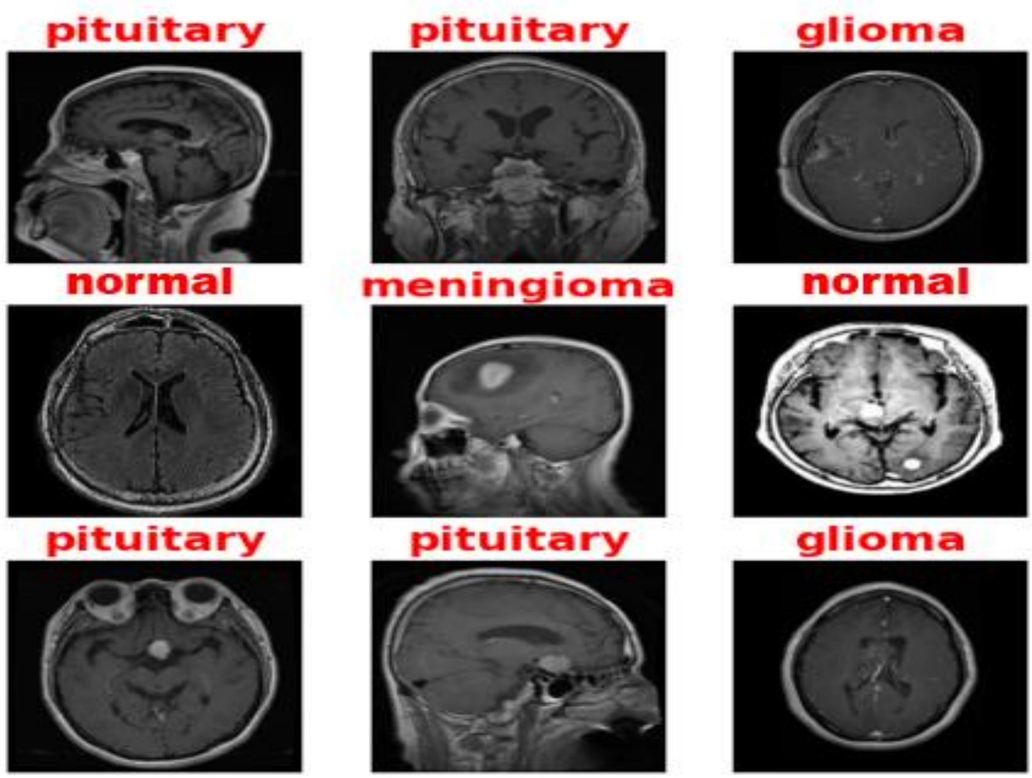


Fig. 2. Samples of the dataset

In Equation (6), recall or sensitivity can be explained as a proportion of true positive values compared to predicted true positive and false negative values. It can be used to assess the completeness of a classifier [29].

$$Rc = \frac{Tp}{Tp + Fn} \tag{6}$$

Additionally, F1-score as indicated in Equation (7), measures the model's accuracy by combining precision and recall. It can be calculated via multiplying precision and recall metrics twice and summing them [30].

$$F1 - score = 2 * \frac{\mathrm{Pr} * Rc}{\mathrm{Pr} + Rc} \tag{7}$$

where, TP refers to true positive which is a set of anomalies that have been identified with the correct diagnosis. True Negative (TN) refers to an incorrectly determined number of regular instances. False Positive (FP) is an accumulation of common instances that are classified as an anomaly diagnosis. False Negative (FN) is a set of anomalies observed as a normal diagnosis. Additionally, confusion matrix is a summary of the predicted outcomes for the classification task. It provides information about not just the errors carried out by the algorithm, along with the sorts of errors made [31].

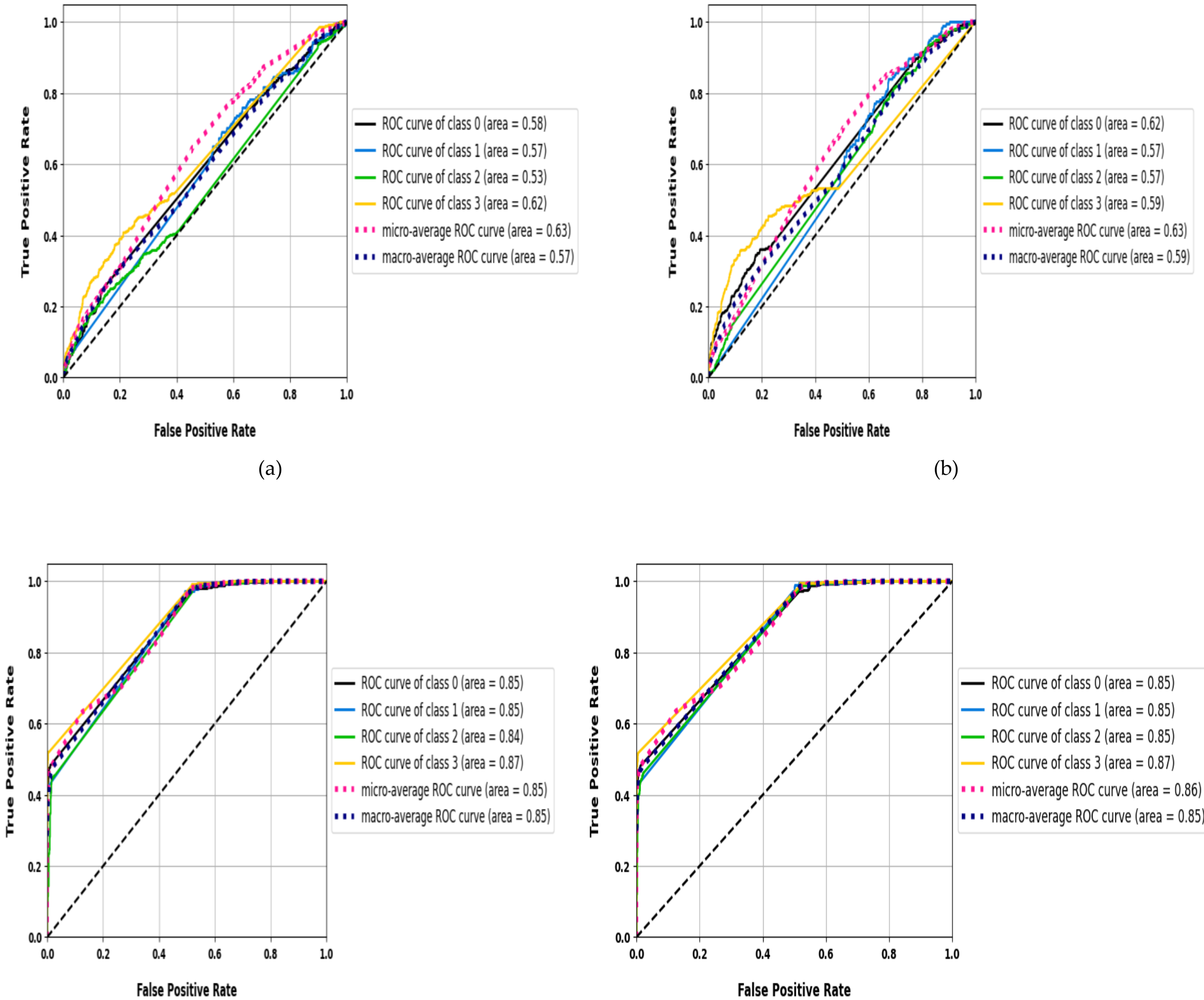
4. Results

This section provides the experimental results and comparative analysis of multiple methods for detecting and classifying brain tumor classes in MRI images. The suggested approach is used to automatically identify and categorize tumor types based on the input dataset provided. In all tests, the model's internal activation function is relu, and the outer activation function is softmax. Several experiments were done in our study. The first experiment was on employing different pretrained models such as ResNet50, Vgg16, Alexnet, and Xception as a feature extractor with LSTM and dropout layers.

In addition, this experiment was done with RMSprop optimizer and 0.0001 for learning rate. Table 2 provides a detailed summary of the experimental findings of the proposed model when applied different pretrained models as feature extractors. From the table, it observed that ResNet50 scored an accuracy value of 87.32% and loss value equal 0.94. In addition, Alexnet achieved low accuracy of 43.70% with high loss of 1.43 as shown in Table 3. Also, fig.3 displays ROC curves for this experiment. Additionally, the second experiment was using traditional ML models as classifiers with ResNet50. It observed that SVM scored high accuracy of 81.46% while RF achieved low accuracy value of 43.70%. On the other hand, the third experiment was training the proposed structure (ResNet50 + LSTM with dropout layers) with different optimizers to evaluate and determine the best performance. As shown from Table 4, the proposed system obtained poor accuracy of 50.31% and high loss of 1.37 with SGD optimizer, but it gained 99.26% and 0.19 for both accuracy and loss of when trained with RMSprop optimizer. Additionally, fig.4 shows ROC curves for this experiment. These findings demonstrate the RMSprop optimizer's superior performance in producing better overall model results.

Table 2: Results for the proposed model when different pretrained models were applied as feature extractor.

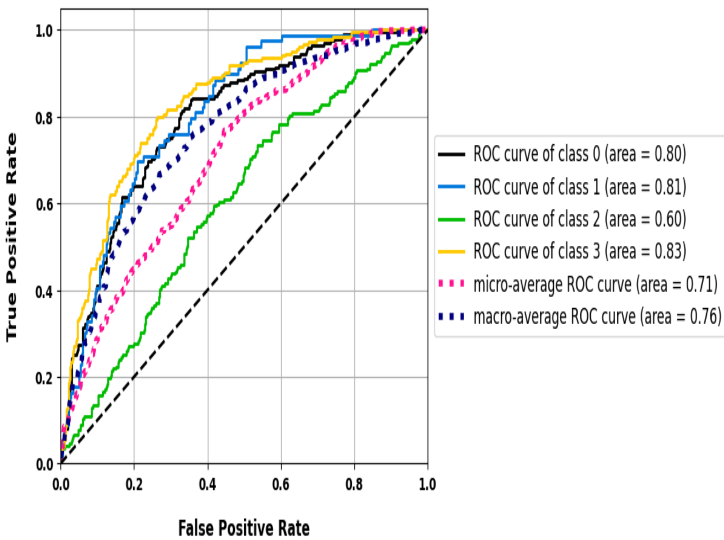
Model	Ac (%)	Pr (%)	Rc (%)	F1-score (%)	Loss
Alexnet	43.70	39.31	32.22	36.94	1.43
Vgg16	52.00	49.18	53.47	51.20	1.32
Xception	81.46	84.90	61.23	71.11	0.81
Resnet50	87.32	84.00	79.69	75.38	0.94



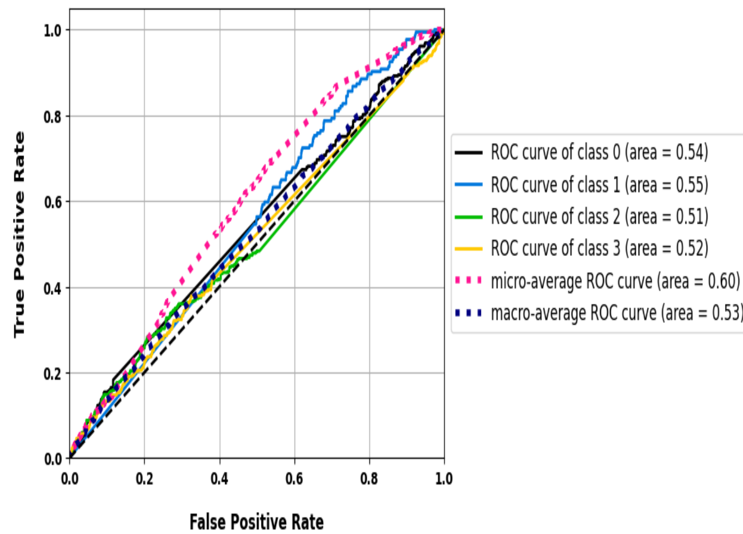
(a) (b)

(c) (d)

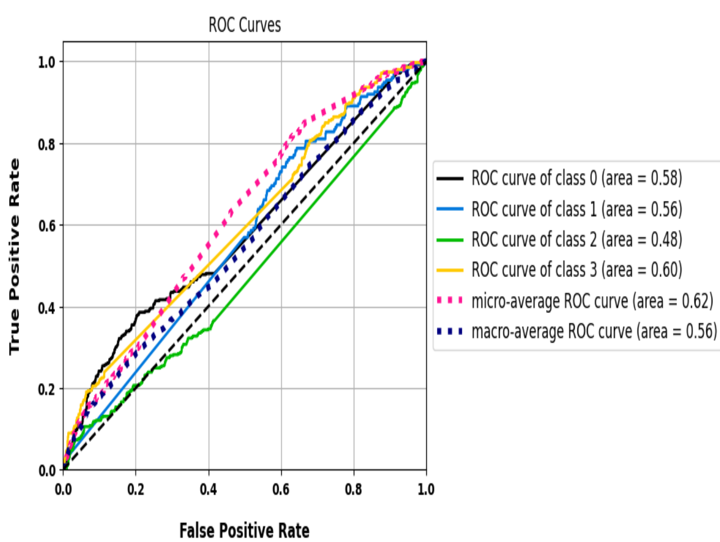
Fig.3. ROC curves of the proposed model when using different pretrained models as feature extractors (a) Alexnet, (b) Vgg16, (c) Xception, and (d) Resnet50.



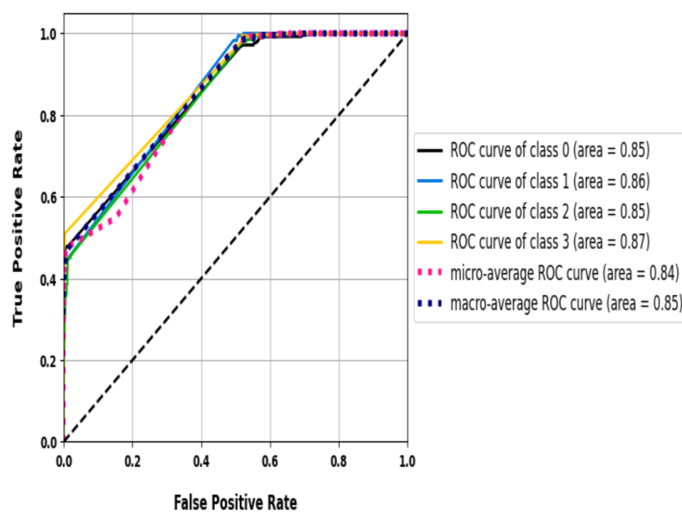
(a)



(b)



(c)



(d)

Fig.4: ROC curves of the proposed model with different optimizers (a) SGD, (b) Adadelta, (c) Adagrad, (d) Adamax, (e) Adam, and (f) RMSprop.

Table 3: Results for ML classifiers with Resnet50 pretrained model was applied as feature extractor.

Model	Ac (%)	Pr (%)	Rc (%)	F1-score (%)	Loss
RF	43.70	39.31	32.22	36.94	1.43
DT	52.00	49.18	53.47	51.20	1.32
SVM	81.46	84.90	61.23	71.11	0.81

Table 4: Results for the proposed model with different optimizers.

Optimizer	Ac (%)	Pr (%)	Rc (%)	F1- score (%)	Losses
SGD	50.31	52.14	48.26	53.83	1.37
Adadelta	56.21	60.89	68.20	66.78	1.39
Adagrad	77.43	76.74	60.72	68.94	0.83
Adamax	93.00	83.00	70.64	76.91	0.43
Adam	97.01	96.73	97.25	96.98	0.22
RMSprop	٩٩,٢٦	98.81	97.74	98.27	0.19

5. **Conclusion and future work**

Brain tumor recognition and classification are vital for prolonging people's life. The goal of this research is to construct an effective model for brain tumor identification and categorization, as well as to improve the accuracy of the classification task. The proposed model developed a combination between ResNet50 pre-trained model and long short-term memory (LSTM). In the hybrid structure, ResNet50 is used for feature extraction and LSTM for classification. We determine the validity of a proposed method using publicly available MRI images. Various metrics and methods are used in evaluation. The outcomes of the experiment show that the strategy we suggested achieved a maximum accuracy of 99.26%. These findings from comparison show that our proposed approach is both effective and advantageous for automatic brain tumor classification. In the future work, we will concentrate on the map reduction framework for big data analytics. Also, we will develop multimodal feature fusion strategy.

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