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Enhancing brain tumor detection: integrating CNN-LSTM and CNN-BiLSTM models for efficient classification in MRI images

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Abstract
Brain tumors are among the leading causes of mortality in humans, characterized by their low survival rates due to the aggressive nature of these tumors. Accurate diagnosis of various malignant and benign brain tumors is crucial. Magnetic resonance imaging (MRI) provides detailed internal views of the human brain, aiding doctors and radiologists in diagnosing brain tumors. However, interpreting MRI images involves complex details that require extensive time and expertise. Artificial intelligence offers solutions to these challenges by simplifying the analysis process. This study aims to develop a fast and accurate system for brain tumor detection. The initial phase of the proposed system involves a segmentation process, where the tumor is distinguished from the background using the fuzzy c-means (FCM) algorithm, resulting in images segmented into foreground and background. These images are then input into the proposed convolutional neural network-long short-term memory (CNN-LSTM) and convolutional neural network-bidirectional long short-term memory (CNN-BiLSTM) models for feature extraction and tumor identification. The goal of this work is to enhance the performance of brain tumor classification and reduce training times. Experimental results demonstrate the effectiveness of the models. The LSTM classifier model was trained in 58 seconds, and the BiLSTM classifier in 91 seconds, achieving accuracies of 97.86% and 99.77%, respectively. However, one limitation noted was the small size of the dataset used in the experiments, which may affect the generalizability of the results.

Keywords
Machine learning, Deep learning, CNN, LSTM, BiLSTM, Tumor detection, FCM.

1.Introduction
Robust computational models such as neural networks were introduced to analyze medical images [1]. Relying on humans single-handedly may cause delay in diagnosis. Because of the anomalous nature of the cancer, it has been considered a curse to humanity [1]. Cancer of the brain is considered the deadliest due to its aggressive nature [2]. It occurs when abnormal cells grow in the brain [3]. An important role was played by brain tumor classification to introduce an accurate diagnosis and treatment [3]. However, magnetic resonance images (MRI) contain complicated details that require a long time and a high-level expert to analyze them, artificial intelligence solves these issues. In traditional machine learning techniques, however, one first needs to extract a vector of features to create a model architecture or machine learning system. To extract this feature vector, specialists in the subject are required. The expert remains busy with these lengthy processes [4]. Because of this, these methods require preprocessing and professional assistance to deal with raw data. However, deep learning (DL) has advanced significantly in solving this issue, with which machine learning researchers have been struggling for a long time. This was made possible by deep networks, which execute the learning process on raw data, as opposed to conventional image processing and machine learning techniques [4]. MRI data is also frequently used for the automatic detection of brain tumors with deep-learning approaches [5]. In addition to diagnosing brain tumors accurately, there is an urgent need for reliable DL, using fine-tuning and extensive pre-processing [6].

Recent studies have focused on the training time of intelligence models. Consequently, this work aims to design a fast and accurate system for brain tumor

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detection. The initial stage of the suggested system involves a segmentation process, where the object is separated from the background using the fuzzy c-means (FCM) algorithm to produce an image with clearly defined foreground and background. This process eliminates additional unnecessary details in the image, which helps improve the quality of extracted features and subsequently enhances the performance of the classifier model. The second stage in this work was the feature extraction stage, convolution neural network (CNN) model was used in this work for this purpose. The final stage of this work was the tumor classification which was done using the long-short-term memory (LSTM) model, and the bidirectional long-short-term memory (BiLSTM) model [7].

The rest of the paper is organized as follows: Section 2 discusses the literature review. Section 3 covers the methods used. Results and their discussion are illustrated in Section 4. Finally, the paper concludes and summarizes in Section 5.

2.Literature review

In the literature, many studies were being conducted on this subject on different datasets. Amin et al. [8] suggest extracting deep features using the inception-v3 model and then feeding them to the classifier, which is a quantum variational classifier (QVR) for tumor classification purposes, the model record detection score is approximately equal to 90%. The experimentation was done on the 2020-BRATS dataset, Cancer Genome Atlas dataset, and locally gathered photos.

Lig and Rahul [3] concentrates on creating reliable segmentation and classification techniques for brain tumor pictures in an attempt to enhance outcomes for patients and decision-making in medicine based on CNN. The work was done on the BRATS 2015 dataset, only the training dataset was used for both training and testing because the testing dataset missing actual labels. The model recorded an accuracy of 77%.

Gómez-guzmán et al. [9] offer the assessment of several deep CNN models for tumor classification purposes like InceptionV3, ResNet50, MobileNetV2, InceptionResNetV2, EfficientNetB, and Xception. The experimentation was done on the Fighshare, Br35H, and SARTAJ datasets. The model score accuracy approximates 97.12% and takes 323 min to train the model.

Mohammed et al. [1] present various systems, including deep, machine, and hybrid models, achieving 99.9% accuracy on a Kaggle dataset. The training time for the model was 114 minutes and 15 seconds. Mahmud et al. [10] proposed a CNN model employing architectures like Inception-v3, Visual Geometry Group 16 (VGG16), and ResNet-50 to effectively identify brain tumors. Their experiments, conducted on a Kaggle dataset, recorded an accuracy of 93.3%.

Gull et al. [11] proposed a framework based on fully convolutional neural networks. The experimentation of the work was done on the dataset namely “BRATS2018”, “BRATS2019”, and “BRATS2020” and the classification accuracy achieved by the model was 96.49%, 97.31%, and 98.79% for the mentioned datasets.

Amran et al. [12] suggest a binary classification model hybrid between the CNN and GoogleNet architecture, the experimentation of the work was done on the Kaggle dataset namely “Br35H”, the model records an accuracy of 99.51%.

Hamran et al. [13] studied the CNN's efficiency with additional skip connections to detect the tumors in the brain from MRI, the work experimentation was done on the Kaggle and “Br35H” datasets and it achieved an accuracy of 99.60%.

Ramtekkar et al. [14] offered a brain tumor detection system that contains preprocessing, extraction of features, and improvement of detection, for brain detection the CNN model was used. The experimentation was done on the Kaggle dataset, and the model had a record accuracy value of 98.9%.

To classify MRI images into meningioma, pituitary, glioma, and no tumor DL models and different machines were proposed by Saeedi et al. [15] such as 2D CNN and auto-encoder, the model experimentation was done on the T1-weighted MRI dataset and it recorded a training accuracy of 96.47% and 95.63% for CNN and auto-encoder respectively.

Irmak [16] offered a brain tumor classification model for multi-classification using CNN for early diagnosis purposes, the experimentation was done on the datasets namely “RIDER”, “REMBRANDT”, and “TCGA-LGG” the model achieved an accuracy of 99.33%.

Zain et al. [17] suggested a CNN-based brain tumor classification model, which uses the "adaptive dynamic sine-cosine fitness grey wolf optimizer" method to improve CNN hyperparameters. The experimentation on the "BRaTS 2021" dataset and the model recorded an accuracy of 99.98%.

Babu et al. [18] use EfficientNets to perform a transfer learning-based fine-tuning method that divides brain cancers into three groups: pituitary tumors, meningiomas, and gliomas. The results showed that the test's overall accuracy was up to 99.06% on the CE-MRI Figshare dataset, which is available to the public.

An accurate brain tumors detection model based on you only look once version 7 (YOLOv7) model was provided by Abdusalomov et al. [19], the experimentation was done on the Kaggle dataset, and it achieved an accuracy of 99.5%. Khaliki et al. [20] proposed a model to classify the brain tumors from the MRI based on CNN, different CNN models were evaluated such as EfficientNetB4, inception-V3 and VGG19. The best accuracy result was obtained with VGG16 with 98%.

From a comprehensive study of different related articles, it is noted that recent studies focus on the training time of the intelligence model and improving the model performance. In addition, It is found that most studies' limitations stem from the insufficient dataset to train the models. *Table 1* shows various methods for classifying brain tumors, the dataset, and the accuracy they recorded.

Table 1 Various methods for classifying brain tumors, the dataset, and the accuracy they recorded

Author	**Year**	**Method**	**Dataset**	**Performance metrics**
Gull et al. [11]	2021	CNN	BRATS2018, BRATS2019, BRATS2020	Accuracy = 96.49%, 97.31%, and 98.79%
Irmak [16]	2021	CNN	RIDER, REMBRANDT, TCGA-LGG	Accuracy = 99.33%.
Amin et al. [8]	2022	Inception V3+QVR	2020-BRATS, Cancer Genome Atlas, Locally gathered photos	Detection score = 90%
Amran et al. [12]	2022	CNN-GoogleNet	Br35H	Accuracy = 99.51%
Zain et al. [17]	2022	CNN	BRaTS 2021	Accuracy = 99.98%.
Babu et al. [18]	2023	EfficientNets	CE-MRI Figshare dataset	Accuracy = 99.06%
Lig and Rahul [3]	2023	CNN (U-Net)	BRATS 2015 dataset	Accuracy = 77%
Gómez-guzmán et al. [9]	2023	CNN	Fighshare, Br35H, SARTAJ	Accuracy = 97.12%
Mohammed et al. [1]	2023	CNN, SVM, ANN	Kaggle	Accuracy = 99.9%
Mahmud et al. [10]	2023	CNN	Kaggle	Accuracy = 93.3%
Hamran et al. [13]	2023	CNN	Kaggle, Br35H	Accuracy = 99.60%
Ramtekkar et al. [14]	2023	CNN	Kaggle	Accuracy = 98.9%
Saeedi et al. [15]	2023	2D CNN, Auto-encoder	T1-weighted MRI	Training accuracy = 96.47% and 95.63%
Abdusalomov et al.[19]	2023	YOLOv7	Kaggle	Precision = 99.5% Recall = 99.3% Sensitivity = 99.3% Specificity = 99.4% Accuracy = 99.5% F1Score = 99.4%
Khaliki et al[20]	2024	CNN2	MRI	Accuracy = 98% F-score = 97% AUC = 99% Recall = 98% Precision = 98%

3.Methods

From a comprehensive study of different related articles, it is noted that recent studies focus on the training time of the intelligence model. Four models were proposed for the classification of brain tumors. The main methodology in this work is divided into three stages:

- FCM: for foreground and background separation.
- Residual Network (ResNet50) [21] for deep features extraction.

- LSTM and BiLSTM training and brain tumor classification.

This work is focused on the assessment of the combination of FCM, CNN, LSTM and BiLSTM for brain tumor detection in MRI. *Figure 1* illustrates the first proposed model. In the second model, the LSTM is replaced by BiLSTM, which includes two LSTMs—one for forward processing and another for backward processing [7]; *Figure 2* depicts this model. The third model combines FCM with CNN and LSTM, as shown in *Figure 3*. The fourth model integrates FCM with CNN and BiLSTM, detailed in *Figure 4*. The comprehensive description of the proposed work is presented in *Figure 5*.

The block diagram of the first proposed model, shown in *Figure 1*, is intended to categorize brain MRI scans as either normal or abnormal, with the anomaly being classified as either a glioma, meningioma, or pituitary tumor. The model is composed of two primary components: an LSTM model and a pre-trained CNN based on the ResNet-50. Features are taken out of the MRI images using the pre-trained model. The LSTM network is then given these features in order to classify the data. The four types of output from the LSTM network are normal, glioma, meningioma, and pituitary tumor.

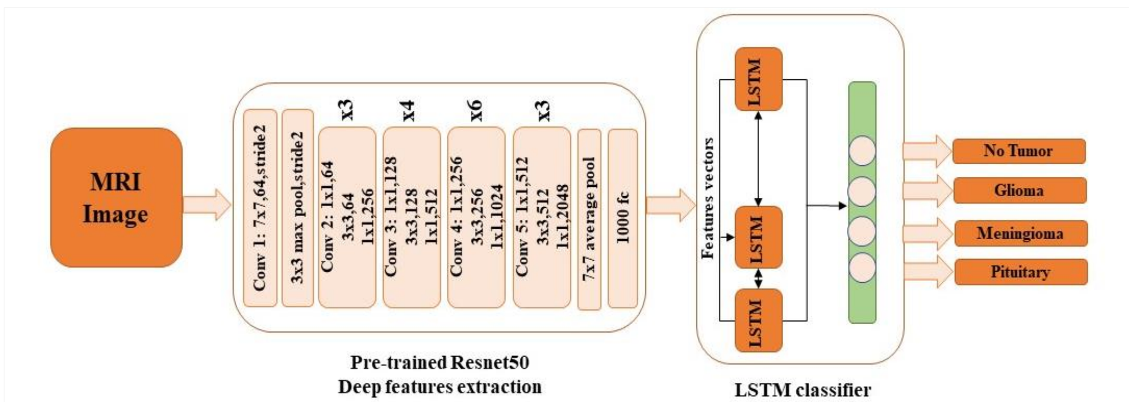


Figure 1 The hybrid CNN-LSTM suggested model

The block diagram of the second proposed model, shown in *Figure 2*, is intended to categorize brain MRI scans as either normal or abnormal, with the anomaly being classified as either a glioma, meningioma, or pituitary tumor. The model is composed of two primary components: a BiLSTM model and a pre-trained CNN based on the ResNet-50. Features are taken out of the MRI images using the pre-trained model. The BiLSTM network is then given these features in order to classify the data. The four types of output from the BiLSTM network are normal, glioma, meningioma, and pituitary tumor.

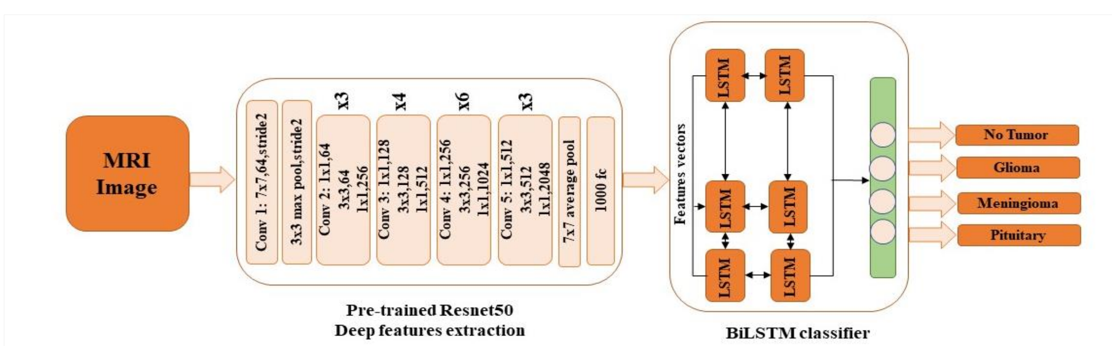


Figure 2 The hybrid CNN-BiLSTM suggested model

The block diagram of the third proposed model, shown in *Figure 3*, is intended to categorize brain MRI scans as either normal or abnormal, with the anomaly being classified as either a glioma, meningioma, or pituitary tumor. The model is composed of three primary components: an FCM, an LSTM model and a pre-trained CNN based on the ResNet-50. FCM was used to detect the tumor region in the MRI and depends on the similarity between each center segment and each pixel in the image to produce an image containing two or more clustering. Features are taken out of the images using the pre-trained model. The LSTM network is then given these features in order to classify the data. The four types of output from the LSTM network are normal, glioma, meningioma, and pituitary tumor.

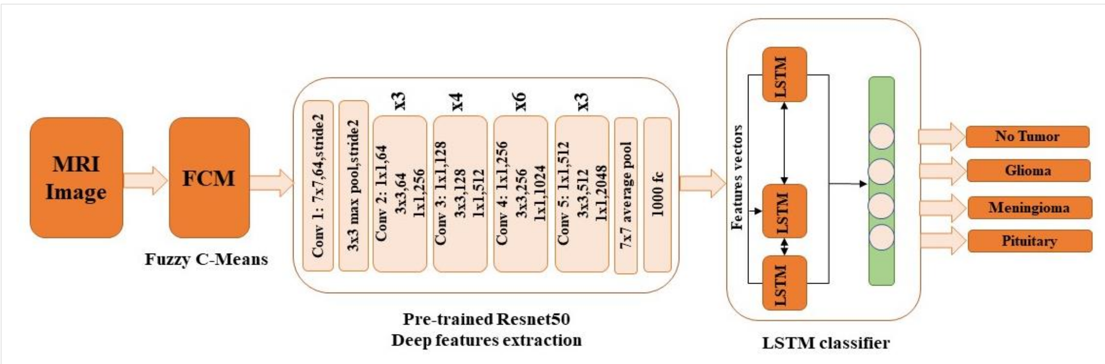


Figure 3 The FCM-CNN-LSTM suggested model

The block diagram of the fourth proposed model, shown in *Figure 4*, is intended to categorize brain MRI scans as either normal or abnormal, with the anomaly being classified as either a glioma, meningioma, or pituitary tumor. The model is composed of three primary components: an FCM, an BiLSTM model and a pre-trained CNN based on the ResNet-50. FCM was used to detect the tumor region in the MRI and depends on the similarity between each center segment and each pixel in the image to produce an image containing two or more clustering. Features are taken out of the images using the pre-trained model. The BiLSTM network is then given these features in order to classify the data. The four types of output from the BiLSTM network are normal, glioma, meningioma, and pituitary tumor.

The suggested models' flowchart is depicted in *Figure 5*. Each image was read from the dataset at the beginning then feed into one of the two routes suggested in this work, which are "Preprocessing 1" and "Preprocessing 2". Preprocessing 1 contains FCM and the resizing operation, while Preprocessing 2 contains the resizing operation only. The output of both routes will feed to the exact features stage to extract the deep features using ResNet50. The classifier is then given these features to classify the data into four types which are normal, glioma, meningioma, and pituitary tumor.

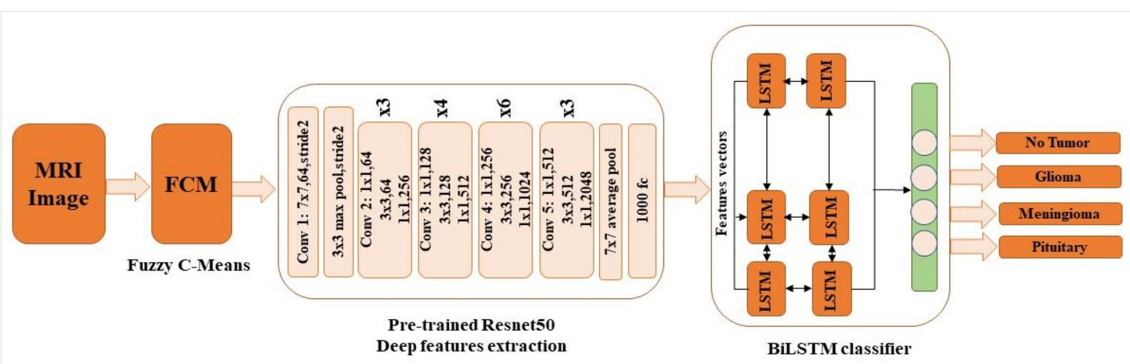


Figure 4 The FCM-CNN-BiLSTM suggested model

3.1Brain tumor Kaggle dataset

For all experiments in this work, the open-access MRI database available in the Kaggle repository was used [22]. This dataset is a combination of the three datasets [9] which are Br35H [23], Figshare [24], and SARTAJ [25]. A summary of the MRI dataset is given in *Table 2*. In this work, for training the classifier model we use 5712 images and 1311 images for testing.

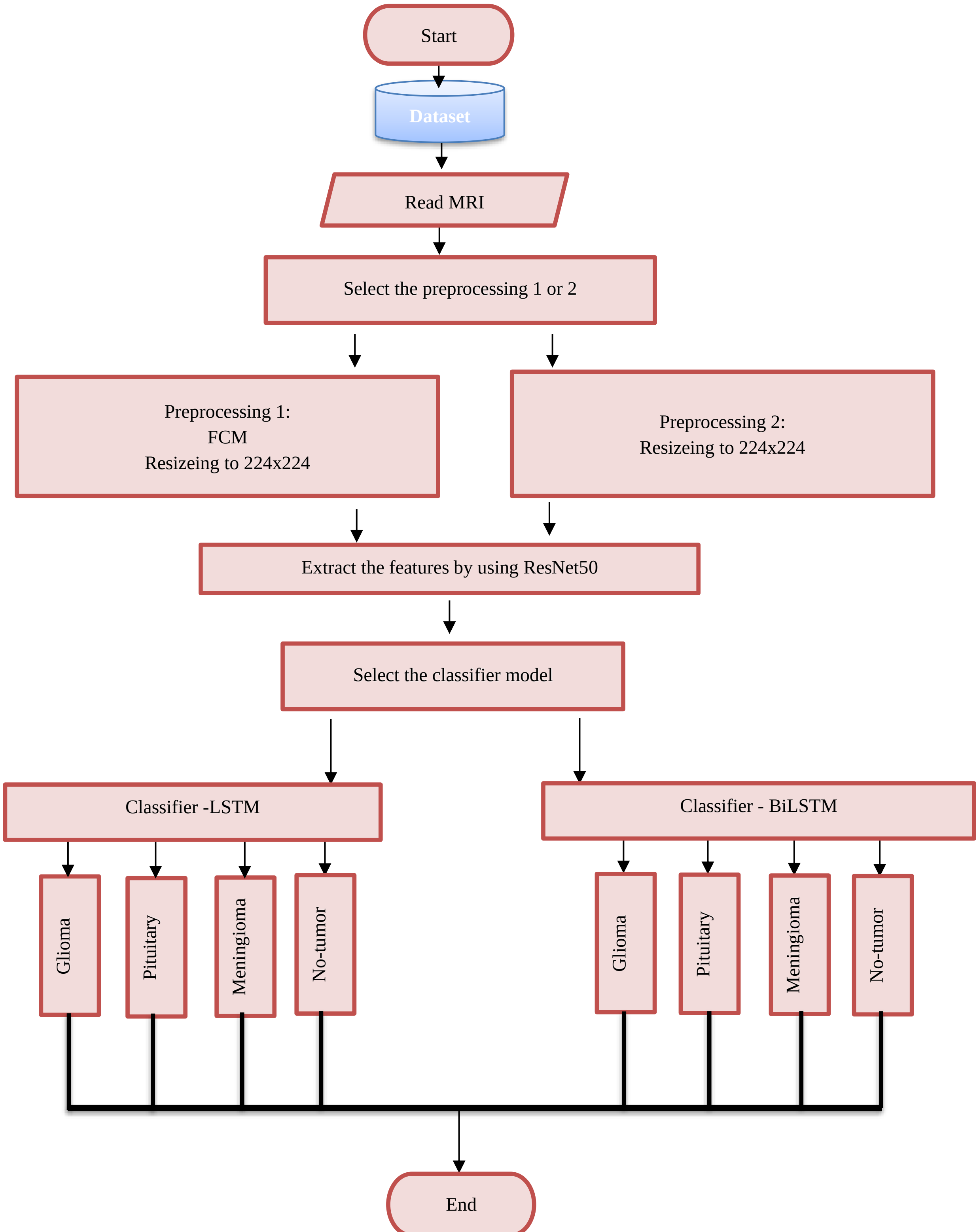


Figure 5 The proposed model flowchart

Table 2 The details of the MRI dataset

Classes	Images for Training	Images for Testing
No-tumor	1595	405
Meningioma	1339	306
Pituitary	1457	300
Glioma	1321	300
Total	5712	1311

3.2Resize image dimension
In this work, a pre-trained model, namely ResNet50, was used for feature extraction purposes; the input size for ResNet50 is 224×224. For this reason, the bicubic interpolation method was used to resize the MRI image size to fit the input model size.

3.3FCM
The most effective known fuzzy clustering technique is FCM [26]. Dunn introduced the FCM in 1973, which was developed in 1981 by Bezdek [27]. FCM is one of the image processing methods used to detect the tumor region in the MRI and depends on the similarity between each center segment and each pixel in the image to produce an image containing two or more clustering [28]. The FCM method divides a finite number of points based on defined parameters into a group of C fuzzy clusters [26]. For sensitive segmentations, such as tissue from the brain models, FCM is often utilized, it can yield superior outcomes when compared to other clustering algorithms [29].

3.4Deep features extraction
This research extracted deep features using a 50-layer deep convolutional neural network namely ResNet50. The input for the ResNet50 model is 224×224 [7]. For each image, the ResNet50 model returns 1000 deep features [7]. These features feed the classifier model for brain tumor classification purposes.

3.5Hybrid CNN with LSTM and BiLSTM
When it comes to the classification of biomedical images, CNN is regarded as one of the top artificial intelligence models. CNN models, however, require computer hardware with high specifications and require training time [1]. To address these issues, a hybrid CNN with LSTM and CNN with BiLSTM approaches are discussed in this section. The suggested framework shown in *Figure 1*, *Figure 2*, *Figure 3*, and *Figure 4* contains the main parts of this work, which are the FCM part, the deep features extraction part, and the classifier part.

In this paper, ResNet50 was utilized as a feature extractor, with features extracted from the fc1000 layers instead of the SoftMax layer. Subsequently, the classifier layer of ResNet50, which is the SoftMax layer, was replaced with LSTM in one instance and BiLSTM in another.

4.Experimental results and discussion
MATLAB software environment (version 2021a) was used for executing the codes. The NVIDIA GeForce MX450 graphics processing unit, the Microsoft Windows 10, 64-bit operating system, Intel Core i7 processor, 16 GB of RAM, and 1 TB SSD hard drive were the essential components of the PC utilized for the task.

4.1Input dataset - brain tumor kaggle dataset
For all experiments in this work, the open-access MRI database available in the Kaggle repository was used [22]. The data is divided into training and testing data. For training the classifier model in this work we use 5712 images and 1311 images for testing the model performance.

4.2Resize image dimensions
In this study, the resizing approach employed was bicubic interpolation, which determines the output using a 16 (4×4 neighborhood) pixel grid. This stage is considered pre-processing for the MRI dataset. The image resizing technique used in this work enhances the classifier model's efficiency compared to the baseline model.

4.3FCM
FCM is an effective categorization technique that allows a data segment to be assigned to two or more clustering centers [30]. FCM produced a binary image containing only the foreground and background for each MRI, specifically images of the brain and the tumor. This step improves the image appearance and aids in extracting better features to represent the images, which leads to enhanced performance of the classifier model.

The resulting image from the FCM stage is passed to the feature extraction stage, which is discussed in the next section. *Figure 6* shows some MRI samples after applying FCM.

4.4Deep features extraction
This research extracted deep features using ResNet50 for each MRI produced from the FCM stage; the features in this work were taken from the SoftMax layer, then fed into the classifier model for brain tumor classification purposes.

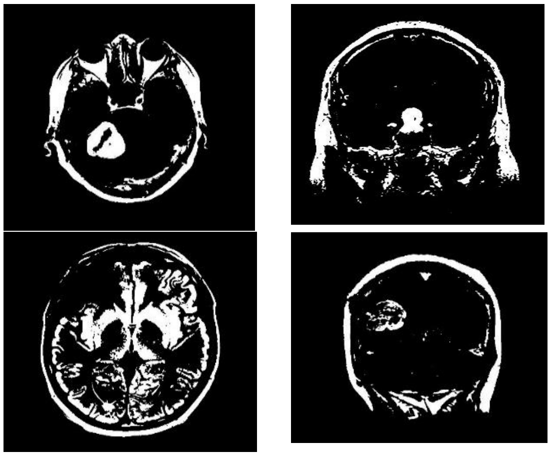


Figure 6 MRI samples after applying FCM

4.5Hybrid CNN with LSTM and BiLSTM

After completing feature extraction, a decision classifier application was necessary. This study utilized LSTM and BiLSTM models as classifiers. Model variables were selected through trial and error using the Adam optimizer, with details listed in *Table 3*. The range for minimum batch size varied from 2 to 256, the number of hidden layers ranged from 1 to 5, the number of nodes in each hidden layer from 10 to 1024, maximum epochs from 10 to 512, and the initial learning rate varied from 0.1 to 1e-7. Where the values that gave the highest accuracy were adopted. The model was trained on 5712 images while testing on 1311 images. Following the previous research [9], the proposed model's effectiveness was evaluated across a variety of performance indicators, the values of all are given in *Table 4*. All classifiers' model's confusion matrix can be shown in *Figure 7*. It is necessary to evaluate the proposed model through prior research after determining the details of the model. A comparison with the previous works has been made in different terms, all of them are listed in *Table 5*. It is observed that the suggested hybrid models score the lowest training time compared with the previous work on the same dataset. In addition, the suggested hybrid models recorded the highest accuracy value up to 99.77% compared to the previous work.

A complete list of abbreviations is listed in *Appendix I*.

Table 3 The suggested model's hyperparameters

The model variables	CNN-LSTM	CNN-BiLSTM	FCM-CNN-LSTM	FCM-CNN-BiLSTM
Optimizer	Adam	Adam	Adam	Adam
Activation function	SoftMax	SoftMax	SoftMax	SoftMax
Initial learning rate	0.001	0.001	0.001	0.0001
L2Regularization	0.0001	0.0001	0.0001	0.0001
Execution environment	GPU	GPU	GPU	GPU
Minimum Batch Size	16	64	16	16
No. of hidden layers	1	1	1	1
No. of nodes in the hidden layer	160	160	160	160
Maximum epoch	60	60	60	60

Table 4 The suggested model's performance

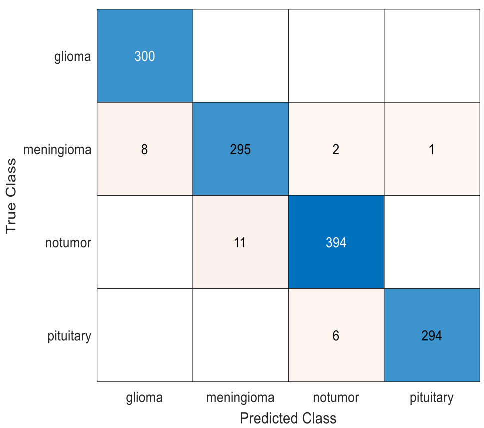
Performance metrics	CNN-LSTM	CNN-BiLSTM	FCM-CNN-LSTM	FCM-CNN-BiLSTM
Accuracy %	97.64	96.57	97.86	**99.77**
Precision %	97.60	97.30	97.87	**99.76**
Recall %	97.90	96.32	97.92	**99.77**
Specificity %	99.22	98.77	99.28	**99.93**
F1score %	97.72	96.66	97.89	**99.76**

Table 5 Comparison of the suggested model performance with previous work

Metrics / method	Accuracy %	F1score%	Training time	Testing time (Seconds)
Gómez-Guzmán [9]	97.12		323 minutes	
Our CNN-LSTM	97.64	97.72	**65** seconds	0.64
Our CNN- BiLSTM	96.57	96.66	**39** seconds	0.89
Our FCM-CNN-LSTM	97.86	97.89	**58** seconds	0.61
Our FCM-CNN-BiLSTM	**99.77**	**99.76**	**91** seconds	0.81

LSTM with accuracy = 97.64%

BiLSTM with accuracy = 96.57



LSTM with accuracy = 97.86%

BiLSTM with accuracy = 99.77

Figure 7 The classifiers model confusion matrix

5.Conclusion and future work

In this research, FCM was used to generate binary images from each MRI as an image preprocessing step. These images were then input into the proposed models, which were based on a hybrid CNN-LSTM and CNN-BiLSTM for deep feature extraction and tumor classification. Specifically, the CNN model, ResNet50, was employed for deep feature extraction. The main objective of this research was to enhance the performance of LSTM and BiLSTM in tumor classification and reduce the classifier model training time. The results demonstrated that the proposed model successfully improved classification performance, with accuracy scores reaching up to 97.86% for LSTM and up to 99.77% for BiLSTM. Additionally, the proposed frameworks were shown to require less training time compared with previous efforts, which needed 58 seconds to train the LSTM model and 91 seconds to train the BiLSTM model, despite the limitation of the data size used. In the future, the suggested models will be evaluated on a large dataset.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability

The MRI dataset utilized in this study is publicly accessible and can be found at https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset.

Author’s contribution statement

Zainab K. Abbas: Conceptualization, Investigation, Data curation, Writing – original draft, Writing – review and editing. **Zaid Ali. Alsarray**: Data collection, Conceptualization, Writing – original draft, Analysis and Interpretation of results. **Adnan Habib Hadi Al-obeidi**: Data collection, Conceptualization, Writing – original draft, Analysis and Interpretation of results. **Mustafa Raad Mutashar:** Study Conception, Design, Data collection, Investigation on challenges and Draft manuscript preparation.

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Appendix I

S. No.	Abbreviation	Description
1	BiLSTM	Bidirectional Long-Short-Term Memory
2	CNN	Convolution Neural Network
3	DL	Deep Learning
4	FCM	Fuzzy C-mean
5	LSTM	Long-Short-Term Memory
6	MRI	Magnetic Resonance Images
7	QVR	Quantum Variational Classifier
8	ResNet50	Residual Network 50
9	VGG16	Visual Geometry Group
10	YOLOv7	You Only Look Once Version 7