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Privacy-Preserving Multi-Class Brain Tumor Classification Using Federated Learning And Deep Capsule Networks

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Abstract

Currently, the Artificial Intelligence (AI) have been widely used in medical imaging for accurate disease classification. However, the currently existing technologies offer centralized learning environments that make them prone to security risks. These security risks may hinder the accuracy of disease classification, leading to a reduced survival rate. To address these issues, a novel multi-class brain tumor classification strategy was proposed in this work using federated learning. The proposed approach integrates the features of Federated Learning with the Deep CapsNet approach (FL-DCN), offering both accuracy and privacy. The proposed framework includes modules: data collection and preprocessing, feature extraction, and classification. In the data collection and preprocessing module, the brain Magnetic Resonance Imaging (MRI) images are collected and preprocessed to ensure consistency and quality. Also, in this stage the collected medical images were effectively pre-processed and enhance the generalizability. In the feature extraction module, a U-Net architecture was employed for extracting the most significant attributes present in the images. Here, dual outcome structure was enabled to implemented the segmentation and feature extraction process simultaneously. The outcomes of this stage is high level feature and tumor masks for CapsNet. In the classification module, a federated learning environment was created and the extracted features are distributed across multiple local nodes. Here, each node has trained three elements such as primary capsules, digit capsules and dynamic routing. Moreover, primary capsules contains 32 capsules and 8D activation vectors; similarly digit capsules consists 4 capsules and 16D vectors for used to match the tumor classes. Consequently, the local node uses Deep CapsNet to learn the spatial and hierarchical patterns within the images. Finally, a Federated Averaging (FedAvg) was employed to combine the model parameters of the local models into a global model, which produces the classification outcomes. The presented methodology is implemented in the Python tool and validated across the public database. The implementation results are determined and validated across the existing technologies in terms of accuracy, precision, recall, f-measure, error rate, and computational efficiency. While comparing the conventional model this study demonstrates that the FL framework can attain privacy protected brain tumor classification from brain MRI image dataset without compromising much accuracy as well as precision parameters.

Keywords: *Federated Learning, Brain tumor Classification, Deep Capsule Neural Network, Disease prediction.*

Introduction

Brain tumor (BT) is one of the deadly diseases affecting millions of people worldwide. It indicates the unusual progression of cells within the brain. The BT can be either malignant or benign, causing serious health issues [1]. Early and precise identification of the boundaries of BT is significant for healthcare institutions for planning effective treatment plans and keeping track of how efficiently work on patients [2]. Currently, various imaging methodologies such as MRI, computed tomography (CT), and X-ray are used for viewing brain tumors and their structures clearly [3]. Among these imaging

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techniques, MRI was widely used by medical professionals or radiotherapists to diagnose brain tumors [4]. By analyzing the brain MRI scan, the doctor categorizes it as either benign or malignant. Benign defines the brain tumor, which is less harmful, while malignant is dangerous and can lead to death if no proper treatment is taken [5].

The advancement of digital technologies has revolutionized the medical sector by introducing automatic disease detection, the internet of medical things, smart healthcare, etc., [6]. In recent years, various degrees of experiments and research have been conducted for detecting brain tumors automatically through artificial intelligence (AI) [7]. The AI technique is a data-driven approach, which uses MRI data for training to differentiate multiple classes of brain tumors. Deep learning (DL), a branch of AI was widely used in disease detection because of its efficiency in thinking and performing like humans [8]. The DL models such as artificial neural networks (ANNs), convolutional neural networks (CNNs), etc., have shown excellent results in BT classification compared to traditional models [9, 10]. However, if the training and testing datasets are smaller, these models produce inaccurate results. Also, they face issues like overfitting, lack of generalizability, larger training time, high hardware and software requirements, etc., [11]. In addition, implementing the DL models in e-healthcare is prone to security, which may lead to misclassification. To address these issues, federated learning (FL) was introduced in e-healthcare [12].

The FL methodology trains the shared global model using data from various institutions in a decentralized manner, ensuring both security and accuracy [13]. In other words, the FL approach is a cooperative training of a machine learning (ML) across a server with a local database gathered from independent devices without exchanging them [14]. In this collaborative training, each local client upgrades the regional model with their data and then sends it to the server for upgrading the global model [15]. This unique feature of the FL approach makes the training more effective and independent. Currently, in the medical sector, the FL framework is applied in numerous applications like medical image classification, image segmentation, disease identification, etc., [16]. In addition, numerous researches have been done in FL to explore in effectiveness in predicting breast cancer, lung cancer, larynx cancer, and prostate cancer [17]. Although the FL approach offers better results than the conventional DL models there are certain challenges, limiting its usage in real-time medical scenarios [18]. Firstly, the FL cannot learn complex and hierarchical patterns within the MRI scans, which reduces its reliability and accuracy in brain tumor classification [19]. The existing FL technique cannot handle the heterogeneity across MRI samples, which degrades the model’s generalizability and induces overfitting [20]. In the medical segments brain tumor detection is essential medical diagnostics. Moreover, early as well as accurate detection has significantly enhance the final outcomes. Consequently, conventional diagnostic strategies are frequently depended on the physical clarification of medical related information, which are time-consuming and disposed to human fault. In the moder era, Artificial Intelligence (AI), mainly deep learning (DL) model, has exposed excessive capacity for systematizing and refining brain tumor analysis in medical information such as MRI scans, etc. Despite these advances may affects a number of problems remain that prevent widespread implementation of DL in therapeutic settings. Consequently, FL model has required constant exchange towards the medical imaging models specially convergence and labeling practices. This has degrade the model performance based on the medical annotations as well as incorrect label reduction. In addition, clinical settings, multi-institutional datasets and medical imaging datasets is difficult due to absence of synthetic federated datasets. to address this issues several approaches are developed such as Convolution Neural network (CNN) is used to differentiate the various types of disease based on the transfer learning model with their layers. Also this model has utilized SMOTE strategy to manage the large data imbalance [21]. Then, data augmentation framework was enabled to enhance the performance of RGB format images based on the transformation parameters [22]. After that, CNN with kernel and stride layer framework is used to tackle the brain tumor classification issues efficiently [23]. These difficulties contain concerns about the data privacy, the requirement for large range of datasets, and the danger of model overfitting due to inadequate data diversity. However, the existing DL models are failed to overcome the issues and provided worst performance in real-world applications. Addressing the issues is significant for accurate and reliable classification of brain tumors. This study proposed an integrated strategy by incorporating the DL model into FL's local model, which enables us to learn the complex and hierarchal feature representation within the MRI samples effectively. But FL has emerged as a feasible decision for handling with these challenges. Also, FL model improves privacy by permitting cooperative typical exercise without the need to disclose raw patient data, while also using the distributed nature of medical data.

The main contributions of the developed work are defined below,

- This study presents an innovative federated learning strategy for classifying different types of brain tumors using MRI scans while preserving privacy and security.
- The presented methodology uses U-Net architecture for image segmentation and feature extraction; this enables the classification model to concentrate on highly relevant and important features during model training.
- The proposed FL strategy integrates a Deep Capsule Network for training the local models effectively to distinguish different classes of brain tumors, offering decentralized training that preserves security and offers improved accuracy.
- The developed methodology was implemented and the achieved experimental results were validated with the existing algorithms in terms of metrics like accuracy, precision, recall, and f-measure.

The organization of the presented article is described as follows: section 2 reviews the recent research works related to this topic, section 3 illustrates the system model and problem statement, section 4 explains the proposed methodology and its working, section 5 examines the results of the study, and section 6 describes the article conclusion.

Related works

Some literature works interconnected with brain tumor classification using the FL approach are described below.

Liping Yi et al [24] presented a semantic image segmentation strategy for the precise identification of BT using MRI samples. This study aims to address the privacy-based restrictions in the deep learning model by designing an optimal FL technique named SU-Net for BT fragmentation. This methodology used the publicly available Brain MRI fragmentation data from Kaggle and achieved a 78.5% dice similarity coefficient, which is greater compared to others. However, this study does not concentrate on multi-class tumor classification.

Divya Peketi et al. [25] developed a reliable solution for tumor segmentation in medical applications. The primary concern of the work is to develop a decentralized fragmentation algorithm using the FL approach for addressing the above issues. This study developed a modified 3D Wasserstein generative adversarial network with gradient penalty (WGAN-GP) and it is integrated at client side of the FL for producing image segmentation pairs. Further, the attention-based 3D-UNet model was designed for segmenting tumor regions from the images. This method offers an 83.56% dice similarity coefficient (DSC). However, the computational complexity is high in this approach.

Y. Nguyen Tan et al. [26] designed a FL model for identifying breast cancer accurately. This study applied transfer learning (TL) for capturing the crucial attributes from the region of interest (ROI), which improves the training efficiency of the system. Consequently, synthetic minority oversampling technique (SMOTE) was utilized for processing data uniformly, which enhances disease prediction, and finally, FeAvg-CNN + MobileNet was developed to ensure data privacy and security. This strategy was validated using the balanced and imbalanced mammography datasets and it achieved higher results compared to DL models. However, integrating multiple techniques into a single algorithm is complex and it lacks interpretability.

Arash Heidari et al. [27] presented a study to identify the location of cancer nodules using the combined efficiency of federated learning and blockchain. This framework uses huge data and utilizes blockchain-assisted FL for training the global DL nodes for classifying lung cancer. This methodology was validated using the Cancer Imaging Archive (CIA) data, and it was implemented in Python. The implementation results manifested that this approach earned 93.12% accuracy in lung cancer detection. However, this strategy demands expensive hardware and software components for real-time implementation.

Bless Lord Y. Agbley et al. [28] presented an innovative approach using the FL algorithm to ensure patient privacy during training. The major motivation behind this work is the privacy concern exhibited in the centralized learning environment of DL methods. Using the FL approach, this methodology aims to accurately classify skin lesions with data privacy. The implementation results validated that only 0.39% accuracy was achieved in DL technique case, while 0.73% accuracy was achieved using the FL framework. However, the multi-level classification of cancer is not discussed in this study.

Daniel Truhn et al. [29] designed an effective solution for addressing the weight update issues in the FL approach. This study developed Somewhat-homomorphically-encrypted federated learning (SHEFL) for effective cancer image analysis with improved security and reliability. In this methodology, the local models of the traditional FL were trained and then homomorphically encrypted to ensure security in the weight update step. The implementation results validated that this strategy offered improved security in e-healthcare applications. However, this strategy does not apply to untrusted servers.

Faizan Ullah et al. [30] developed a BT fragmentation model to help healthcare professionals in identifying and treating BT in their early stages. AI-assisted imaging applications often face problems in data sharing, limiting their real-world applications. This study utilized the FL algorithm to address this issue by providing collaborative learning using disseminated data from different healthcare organizations without sharing raw data. The experimental assessment validates that this strategy offered an improved specificity of 0.96 and a DSC of 0.89 for an increasing clients.

Zhipeng Fan et al. [31] designed a FL framework for addressing the issues of DL in healthcare image processing. Typically, aggregating medical images from multiple sites is complex, which restricts the DL model's applicability in e-healthcare applications. This study modeled a Guide-Weighted Federated FL mechanism for multisite 3D brain MRI images to ensure accurate disease prediction. This study used the brain MRI data of Autism Spectrum Disorder (ASD) - ABIDE I&II and obtained 0.92% accuracy. However, this strategy faces issues like computational overhead and large energy consumption.

Cuneyt Ozdemir et al, [23] have developed the CNN based transfer learning framework to detect and differentiate the various stages as well as types of Alzheimer’s disease. Moreover, this model initially capture the early symptoms such as severe dementia of the Alzheimer’s disease. Also, SMOTE and Avg-TopK pooling layers are structured to manage the data imbalance issues. Moreover, ablation study was conducted to highlight the effectiveness pf the developed model. classification process is done with the help of Grad-CAM analysis for demonstrated the overall significance of the diagnostic platform. However, each classification and detection iterative process take too much time.

Table.1 Summary of related works

Sl.no	Author name	Techniques	Merits	Limitations
1	Liping Yi et al [24]	semantic image segmentation strategy	achieved a 78.5% dice similarity coefficient, which is greater compared to others	this study does not concentrate on multi-class tumor classification
2	Divya Peketi et al. [25]	WGAN-GP	This method offers an 83.56% dice similarity coefficient (DSC)	the computational complexity is high in this approach
3	Y. Nguyen Tan et al. [26]	TL with SMOTE	it achieved higher results compared to DL models	integrating multiple techniques into a single algorithm is complex and it lacks interpretability

4	Arash Hedari et al. [27]	CIA	this approach earned 93.12% accuracy in lung cancer detection	This strategy demands expensive hardware and software components for real-time implementation
5	Bless Lord Y. Agbley et al. [28]	FL algorithm	0.73% accuracy was achieved using the FL framework	the multi-level classification of cancer is not discussed in this study
6	Daniel Truhn et al. [29]	SHEFL	This strategy offered improved security in e- healthcare applications	this strategy does not apply to untrusted servers
7	Faizan Ullah et al. [30]	BT fragmentation model	improved specificity of 0.96 and a DSC of 0.89 for an increasing clients	Higher error rate for using this strategy
8	Zhipeng Fan et al. [31]	FL framework	Effectively addresses the heterogeneous issues and enhance the accuracy	this strategy faces issues like computational overhead and large energy consumption
9	Cuneyt Ozdemir et al, [23]	CNN based transfer learning framework		each classification and detection iterative process take too much time

The above literature are discussed about the conventional FL with brain tumor detection and classification performance across the various domains. However, that are lacking to integrated the privacy preserving model for medical imaging. FL model based on healthcare application cannot focus heterogeneous data for detecting brain tumors. Moreover, DL based tumor detection frameworks has lacks the privacy concerns depend on centralized algorithms. Also, this model has failed to manage the non-IID data for communication and cannot tailored the specific challenges.

System model and problem statement

BT is one of the deadliest diseases globally, affecting thousands of people. It is generally defined as an unusual growth of tissues within the brain. The early and accurate diagnosis and classification of brain tumors is important for saving lives through proper treatment planning. Currently, DL methodologies have earned more attention in automatic disease classification field. However, there is a need for huge data to train the DL for precise training. Also, the training in DL models is centralized which makes them prone to security breaches in e-healthcare applications. The intrusion of medical data may lead to inaccurate diagnoses, affecting the patient's health. Addressing these challenges in the DL models is crucial for reliable BT prediction and classification in real-world scenarios. FL, a branch of ML paved the way for addressing these issues by offering collaborated learning through decentralized training. In the FL model, there are numerous local models and a single global model. The regional models are trained using distributed local dataset independently, while the worldwide model produces the final classification result by aggregating the predictions of the local models. This way of classification reduces the security threats since it does not involve the exchange of information. However, the FL methodologies cannot understand the complex patterns and feature representations in the MRI scans, which minimizes its classification accuracy. To address this issue, an innovative FL methodology was proposed by incorporating a DL into the local models of FL for learning complex data patterns. Additionally, the proposed method uses extracted feature sequences for model training, making the learning process simple and effective. Figure 1 presents the system model of FL-based brain tumor classification.

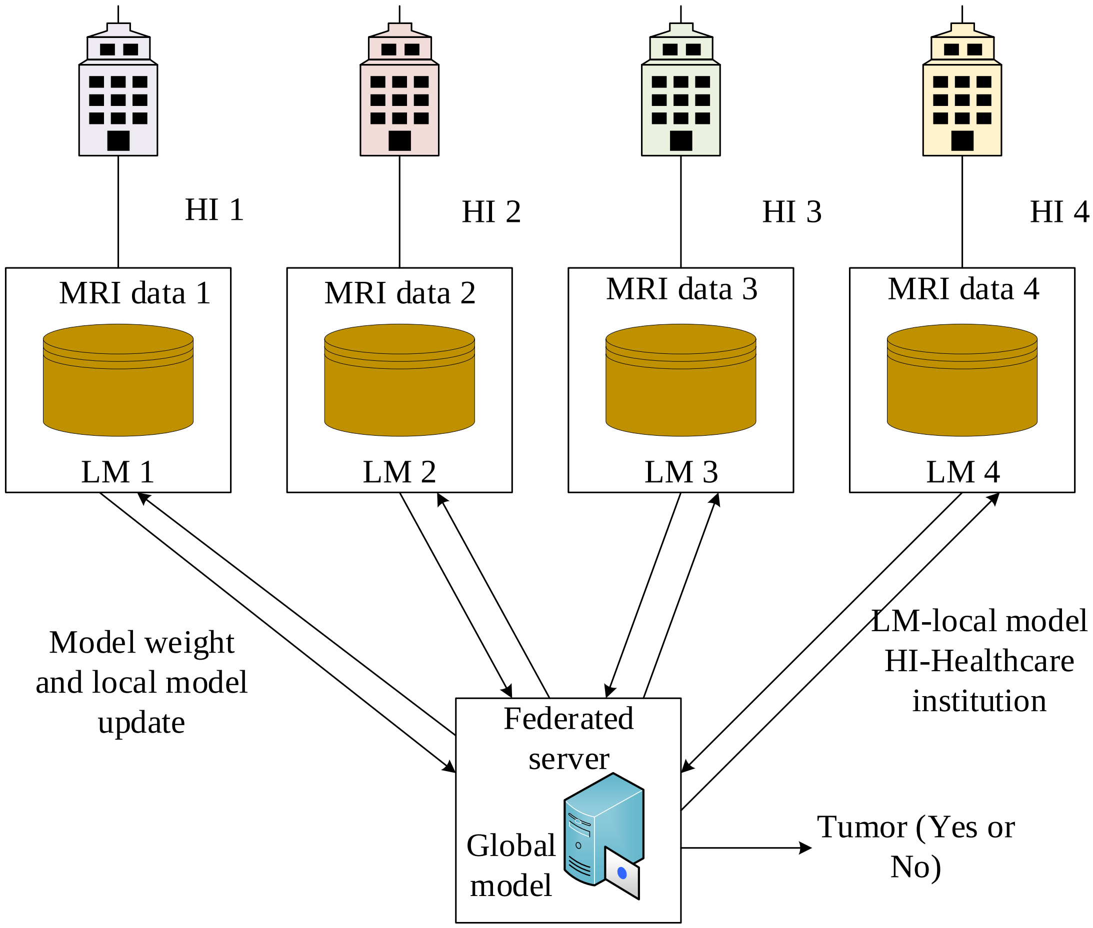


Figure 1: System model

Proposed methodology for BT classification

This section discusses the working of the proposed framework for the classification of BT. The framework includes five phases: Image accumulation, preprocessing, feature engineering, model training, and BT categorization. In the data collection phase, the brain MRI image samples are gathered and fed into the system. Consequently, in the preprocessing phase, all input images undergo steps like filtering, contrast enhancement, and segmentation; these steps make the input images appropriate for further analysis. In the feature extraction phase, U-Net architecture was employed for segmenting the image and capturing the most informative attributes from the segmented images. In the model training phase, a federated learning environment was constructed and each local model in FL was trained using the extracted feature sequences by utilizing the Deep CapsNet algorithm. This decentralized way of learning not only understands the patterns and correlations within the images but also reduces security threats. In the classification phase, all the learning outcomes of the LMs are combined into a global model using the FedAvg, which produces the final BT classification output. Moreover, the developed FL model has attained two significant functions such as semantic abstraction as well as data minimization for managing the sensitive information from the data. Also, Deep CapsNet and FedAvg modules was utilized to extract the features during the training process. Consequently, this model has enhanced the overall security performance for processing the medical imaging by applying the privacy preserving criteria and logically protecting off numerous classes of adversarial threats. The developed model's architecture is portrayed in Figure 2.

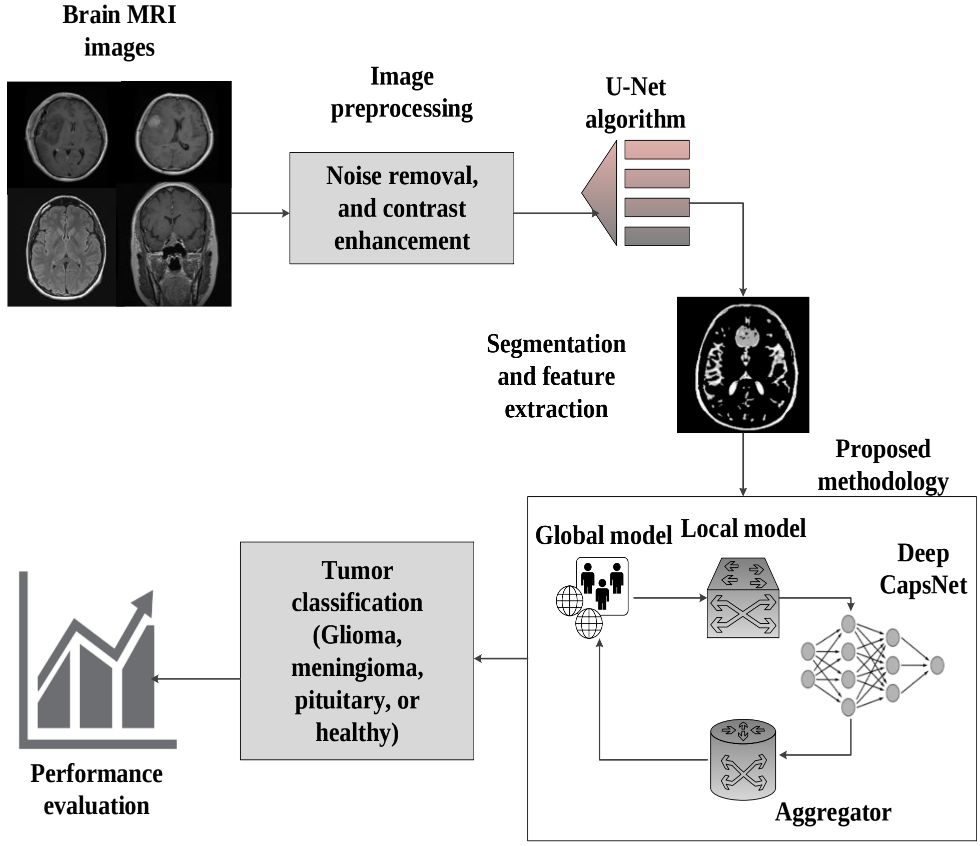
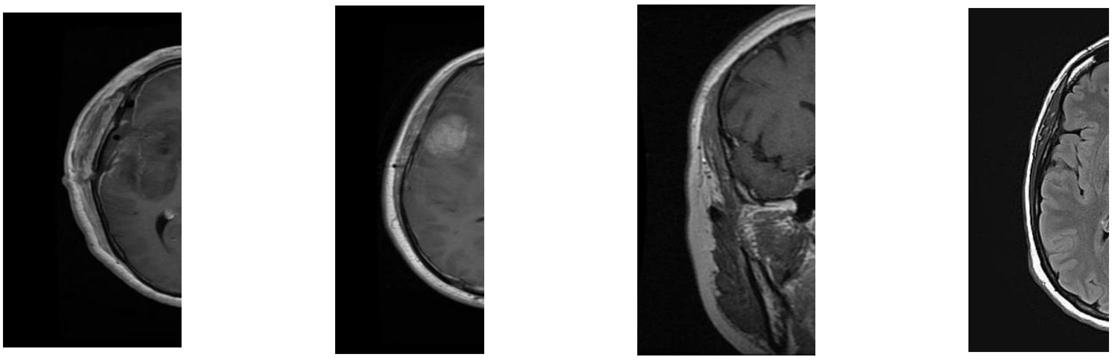


Figure 2: Architecture of the proposed strategy

Data collection

BT classification begins with the accumulation of brain MRI samples from the individuals (patients and normal). The collected images are then annotated by medical professionals or radiotherapists to train the ML model effectively. The presented study utilized the publicly available brain MRI database named "Brain Tumor (MRI scans)" from the Kaggle site and it can be assessed on [32]. This dataset contains 7023 MRI images that are categorized into four classes namely: glioma (1621), meningioma (1645), pituitary (1757), and healthy (2000). The total size of the dataset is 261.98 MB and the primary objective of creating this dataset is to save patient lives through timely identification of brain tumors. This dataset is preprocessed and then split into the ratios of 80:20 for training and testing purposes. Figure 3 presents the sample images of the dataset.



(a) (b) (c) (d)

Figure 3: Sample dataset images: (a) Gioma, (b) Meningioma, (c) Pituitary, and (d) Healthy

Data preprocessing

Data preprocessing defines the process of enhancing the quality and consistency of the raw MRI scans. In the preprocessing phase, the images undergo steps like image resizing, noise removal, contrast enhancement, and segmentation. The MRI images in the input dataset are of different sizes, which induces inconsistency issues during model training. In the image resizing step, all images in the dataset are resized into a constant size [n x n] by performing either scaling or cropping. Following image resizing, noise removal was performed using a Gaussian filter. Typically, the scanned images contain some unwanted random variations (noises), which reduce the accuracy of the model in BT classification. These random variations are due to numerous factors like long exposure times, poor lighting conditions, etc. In Gaussian filtering, the average value of the neighboring pixels replaces the noisy pixel based on Gaussian distribution, and it is formulated in Eqn. (1).

$$Gu(a,b) = \frac{1}{2\pi\sigma^2} e^{-\frac{a^2+b^2}{2\sigma^2}} \tag{1}$$

Where $Gu(a,b)$ indicates the Gaussian function at coordinates (a,b) and σ represents the standard deviation. Then, the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm was used for contrast enhancement. This step helps in enhancing the visibility of specific structures within the MRI samples. The CLAHE approach works on a small region of the image (tiles) rather than the whole image, and the neighboring tiles are blended using bilinear interpolation to eliminate the false boundaries. The steps of the CLAHE algorithm are described below.

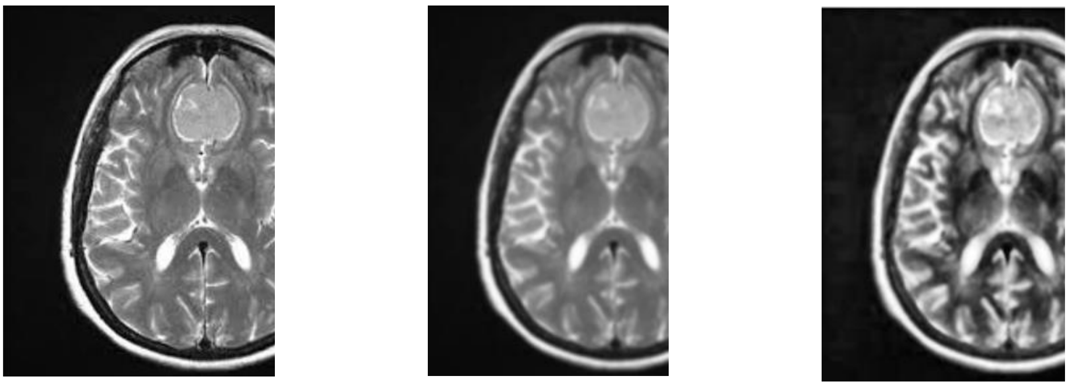
Step 1: Divide the input image into smaller non-overlapping regions (tiles).

Step 2: Estimate the histogram for each tile, which measures the intensity distribution within that region.

Step 3: Apply histogram equalization with each tile to improve the image contrast.

Step 4: Finally, contrast-limited clipping was done histogram to prevent over-amplification of noises.

These steps improve the contrast of the input MRI scans. Figure 4 presents the input image and its corresponding preprocessed images. These preprocessing steps not only enhance the classification accuracy but also aid in reducing the computational time required by the classifier to process the data.



(a) (b) (c)

Figure 4: Preprocessing outcomes: (a) Input, (b) noise removal, (c) contrast enhancement

Finally, the images were normalized and resized using the normalization function, here, the pixels are scaled between 0 to 1 range. then, the images are resizing using 128×128 pixel resolution which is used to ensure the consistency of the models based on below eqn. (2),

$$y' = \frac{y - \min\ (y)}{\max\ (y) - \min\ (y)} \tag{2}$$

where, y' is demoted as pixel value with respect normalization function; here, overfitting issues are managed by increasing the data diversity and zooming performance.

Segmentation and feature extraction

Segmentation indicates the process of segregating the preprocessed MRI scans into various areas (segments) for reliable tumor classification. In other words, it defines the process of isolating the important brain tissues from the background. On the other hand, feature engineering defines the procedure of capturing highly correlative attributes in the segmented image for model training. In the developed work, the U-Net algorithm was employed for performing both segmentation and feature extraction tasks. This algorithm has 3 units namely: encoder, bottle-neck, and decoder.

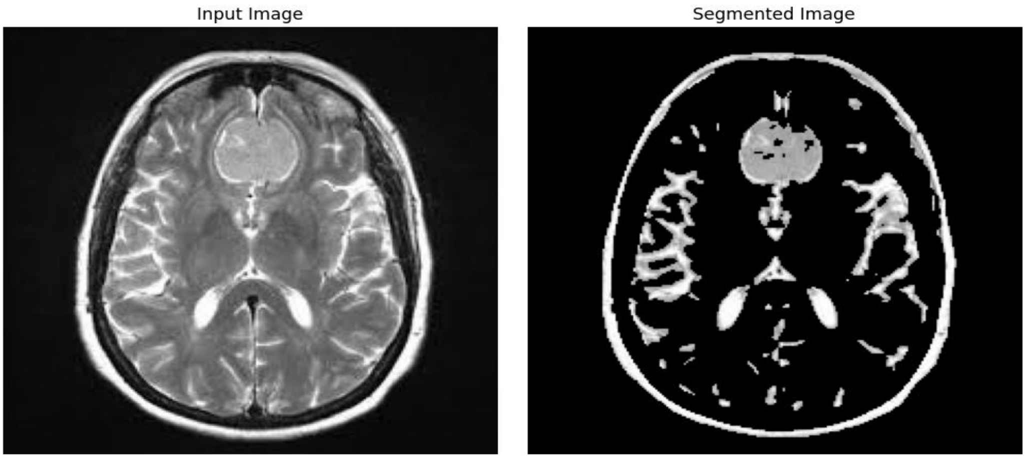


Figure 5: Image segmentation

The encoder unit contains a dense convolutional and pooling layer that performs a down-sampling function. This down-sampling process provides the segmented images by removing the unwanted background regions while preserving important spatial and temporal features. This segmented image is forwarded into the bottle-neck unit (deep neural network). This component analyzes the segmented image and captures the high-level attributes from it. Finally, the decoder unit performs a deconvolution operation and returns only relevant and important features such as shapes, edges, boundaries, size, intensity, etc. This extracted feature sequence is then forwarded into the proposed algorithm for model training. Figure 5 presents the input and its segmented images.

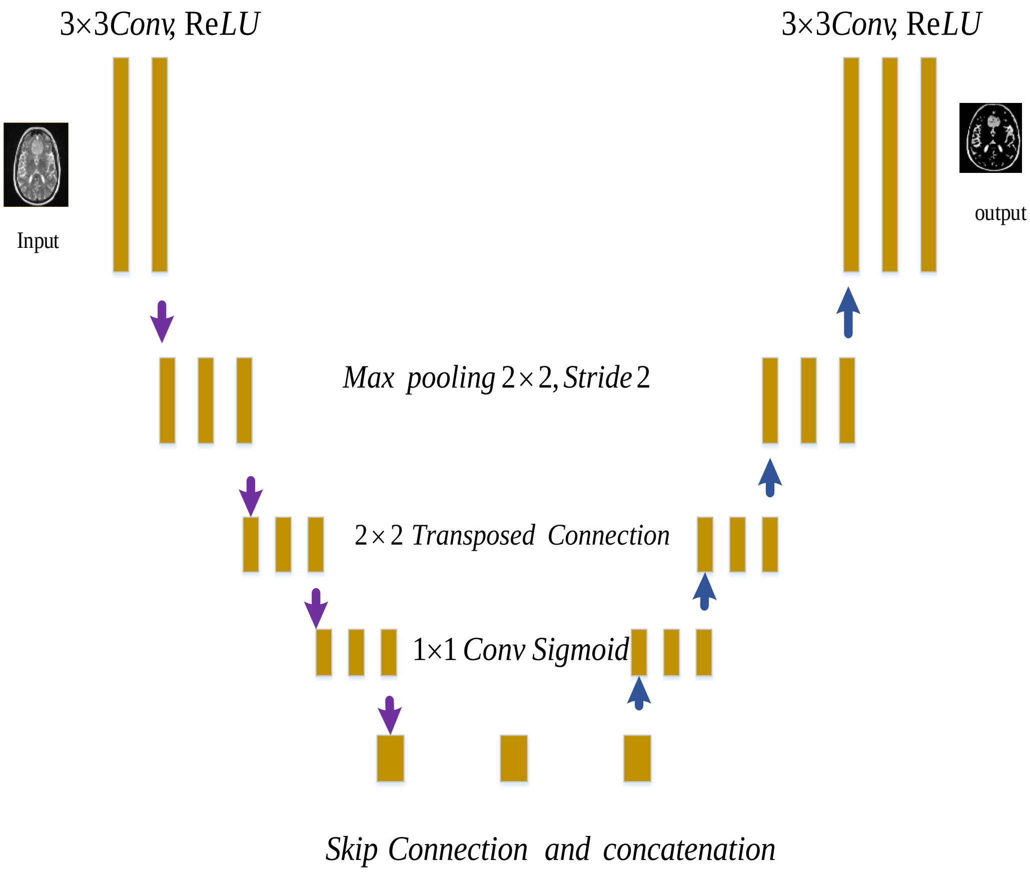


Fig. 6 Schematic diagram of the U-Net model

Federated Learning

FL is a ML technique in which a model is trained across numerous decentralized servers by holding local data samples without sharing them. The primary motivation behind this approach is to preserve privacy while achieving greater accuracy in brain tumor classification. This methodology reduces the need for data transmission and centralization, ensuring security within the data-driven framework. The basic concept of the FL framework involves training local models on individual devices and then aggregating these models to update the global model [30]. In the proposed methodology, the training of the regional models was governed by the Deep Capsule Neural Network (CapsNet), which enables the models to learn the spatial and hierarchical patterns within the data [31]. This learning makes each local model produce classifications which are then aggregated using FedAvg to update the global model. A federated learning environment was created in which the global model parameters are denoted g_w. The total number of devices participating in the training is denoted as m and each device d_v has a local database (subset of extracted feature sequence (f_s) with m_v samples. This training progress follows the Deep CapsNet algorithm. Moreover, the FL model has follows client-server training process based on the steps,

Step:1: Deep CapsNet consists clients which are trained and locally it have the own data
step:2: Then, the own data weights are transferred through the central server
step:3: Then, the servers are enabled to collective the data without support of raw data
step:4: Finally, the global model has updated the function with cross entropy model.

Deep CapsNet algorithm-based training

Moreover, Deep CapsNet paradigm can replace the conventional convolutional layers with that encoder function both spatial as well as probability relationship of features. Here, initial layer is convolutional layer used to extract the feature based on filters 256 and size 9×9. Then, convolutional layer's output s are passed through the primary capsule layer. after that, decoder network layer is enabled to reconstruct the input images to normalize the model. Capsules define the group of neurons where its activity vectors indicate pose parameters and the length denotes the probability that a specific entity exists. The CapsNet algorithm was developed to address the issue related to the pooling layer of the CNN. In this algorithm, the pooling layer is replaced with a criterion named "routing by agreement," and the outcomes are forwarded into the parent capsules based on this criterion in the next layer. Each capsule intends to forecast the parent capsule's outcome and if the prediction matches with the real output of the parent capsule, the coupling coefficient between the two capsules increases. The prediction for the parent capsule p by the capsule q is determined using Eqn. (2).

$$y'_{p/q} = \lambda_{p,q}\, y_q \tag{2}$$

Where $y'_{p/q}$ defines the output prediction vector of p^{th} the capsule in a higher level determined by the capsule q in the below layer, y_q denotes the q^{th} capsule's outcome, and $\lambda_{p,q}$ represents the weight matrix. Further, the coupling coefficient was computed based on the correlation between the predicted results of the capsules, as defined in Eqn. (3).

$$Cf_{p,q} = \frac{\exp(\kappa_{q,p})}{\sum_r \exp(\kappa_{q,r})} \tag{3}$$

Where $\kappa_{q,p}$ indicates the log probability which determines whether the capsule q can be coupled with p it is set as zero in the initial phase of routing by agreement process. The parent capsule's input vector is represented in Eqn. (4).

$$In_p = \sum_q Cf_{p,q}\, y'_{p/q} \tag{4}$$

Then, a non-linear squashing function was employed to prevent the capsule's output vectors from exceeding 1. The resultant of each capsule by its initial vector is defined in Eqn. (5).

$$Ov_p = \frac{\|In_p\|^2}{1+\|In_p\|^2}\frac{In_p}{\|In_p\|} \tag{5}$$

The log probabilities are updated in the routing process based on the agreement between the final resultant Ov_p and the output prediction vector of the p^{th} capsule $y'_{p/q}$. This agreement is based on the fact that if they are relevant or similar (vector matches), they will have a large inner product. The agreement updating coupling coefficient and log probabilities are computed using Eqn. (6).

$$\chi_{p,q} = Ov_p \,.\, y'_{p/q} \tag{6}$$

This process continues iteratively and each iteration of the Deep CapsNet aims to improve the agreement efficiency. This routing agreement enables the capsules to update their learning, making it to effectively differentiate BT classes. Following this routing mechanism, the capsule r in the final layer produces a classification outcome, which indicates whether the input image belongs to “glioma”, “meningioma”, “pituitary,” and “healthy.” Each capsule r in the final layer is interconnected with a loss function L_r, and it is mathematically calculated using Eqn. (7).

$$L_r = T_r \max\left(0, j^+ - \|Ov_r\|\right)^2 + \eta\left(1-T_r\right)\max\left(0, \|Ov_r\| - j^-\right)^2 \tag{7}$$

Where L_r indicates the loss function of the capsule r in the final layer, T_r denotes the presence of the predicted class (if it is equal to 1, then it defines the presence of the predicted class and if it is equal to 0, it denotes the absence of the predicted class in the dataset) j^+, j^- and η indicates the hyperparameters of the Deep CapsNet model that will be updated iteratively for improved training. By following the Deep CapsNet training, all the local models in the FL environment get trained to distinguish the multiple tumor classes. Each device d_v computes its local loss function similar to the loss function of Deep CapsNet and the local models update their parameters to reduce this loss iteratively. Finally, the LMs send their classification outcomes to the central server, which combines these outcomes using FedAvg. The combined result is forwarded into the global model, which produces the final classification outcome, which is mathematically presented in Eqn. (8).

$$Gm_c(im) = \begin{cases} if\left(Ar_o(im) = -1\right); Glioma \\ if\left(Ar_o(im) = 0\right); Healthy \\ if\left(Ar_o(im) = 1\right); Meningioma \\ if\left(Ar_o(im) = 2\right); Pituitary \end{cases} \tag{8}$$

If the aggregated value $Ar_o(im)$ of the image is -1, the global model predicts the image as "Glioma", while $Ar_o(im)$ is equal to 0, then the model classifies it as "Healthy". Similarly, if the $Ar_o(im)$ is 1, then it categorizes the image as "Meningioma" and if $Ar_o(im)$ is 2, then it predicts it as "pituitary". The classification error can be determined by estimating the loss function of the global model, as expressed in Eqn. (9).

$$L_{gw} = \sum_{i=1}^{m} \frac{m_v}{m} L_{lmi} \tag{9}$$

Where the loss function of the global model is represented as L_{gw}, which is determined by taking the weighted sum of the loss function of local models L_{lm}. In each iteration, the FL approach intends to reduce this global loss function by updating its parameters optimally using the Adam optimizer. Thus, the proposed strategy accurately classifies the brain tumor classes using MRI scans. The working of the developed algorithm is presented in pseudocode format in algorithm 1.

Algorithm:1	
Input: Brain MRI samples;	
Output: Glioma or Meningioma or Pituitary or Healthy;	
Start {	
Initialization: // MRI image (im), global model parameters (g_w), local model parameters(l_w), maximum iteration($T_{\max}$), Deep CapsNet parameters, and number of devices(m);	
for each iteration	
	$t = 1, 2, 3, 4, ...T_{\max}$
	do
for each device $d_{vi} \in 1, 2, 3, 4, ...m$:	
Initialize local model parameters l_w ;	
Train each local model using Deep CapsNet with f_s ;	
For each training epoch $eh = 1, 2, 3, 4, ...e\max$:	
Determine capsule activity vectors using routing-by-agreement;	
Apply non-squashing function;	
Estimate prediction vector and update coupling coefficient;	
Commute the classification outcome of the capsule and determine its loss function L_r ;	
Update classification results of LMs and send them to the central server;	
End for;	
Aggregate local model results using FedAvg;	
Perform final BT classification using Eqn. ();	
Determine the loss function of the global model L_{gw} ;	
Update global model parameters using Adam optimizer;	

End for;
End for;
} **End**

Results and discussion

This study proposed a federated learning strategy for the classification of brain tumors by analyzing the brain MRI samples. The presented approach was implemented on Python version 3.12.6 running in Jupyter Notebook 7.12, and supported by a Dell 11th Generation processor with 8GB RAM. The developed model's performances are determined and validated with the existing BT classification models using parameters like accuracy, precision, recall, and f-measure.

Evaluation parameters

The parameters used for determining the model's performances include accuracy, precision, recall, and f-measure and they are defined below.

Accuracy:

Accuracy quantifies the overall correctness of the framework in categorizing BT types. It is determined by quantifying the proportion of correctly classified instances to the total instances and is described in Eqn. (10).

$$Accuracy = \frac{T_{ps} + T_{nv}}{T_{ps} + T_{nv} + F_{ps} + F_{nv}} \tag{10}$$

Where T_{ps}, T_{nv} F_{ps} and F_{nv} defines the true positive (TP), true negative (TN), false positive (FP), and false negative (FN), respectively.

Precision:

Precision defines the model's capacity to correctly detect the T_{ps} cases. It is determined by measuring the ratio of correct T_{ps} predictions among all the positive predictions made by the system, and it is formulated as Eqn. (11).

$$\Pr ecision = \frac{T_{ps}}{T_{ps} + F_{ps}} \tag{11}$$

Recall:

Recall defines the model's effectiveness in finding all related instances for accurate BT classification. It is determined by evaluating the ratio of true positives among all real positives and it is mathematically represented in Eqn. (12).

$$\operatorname{Re} call = \frac{T_{ps}}{T_{ps} + F_{nv}} \tag{12}$$

F-measure:

F-measure represents the harmonic mean of both recall and precision parameters. It offers a sensible evaluation of the system's classification outcomes considering both positive and negative instances, and it is represented in Eqn. (13).

$$F - measure = 2 \times \left(\frac{\Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \right) \tag{13}$$

The evaluation of these parameters offers a comprehensive evaluation of the proposed technique's efficiency in identifying and classifying the BT instances.

Model training and testing

In ML, training and testing the model is crucial for interpreting how efficiently it learns and the patterns within the MRI images for accurate BT classification. Firstly, the input brain MRI data was divided in which 80% for training and 20% for testing, and the initial parameters of the model were defined. The training and testing efficiencies are determined in terms of metrics like accuracy and loss over the increasing epoch from 0 to 17.5.

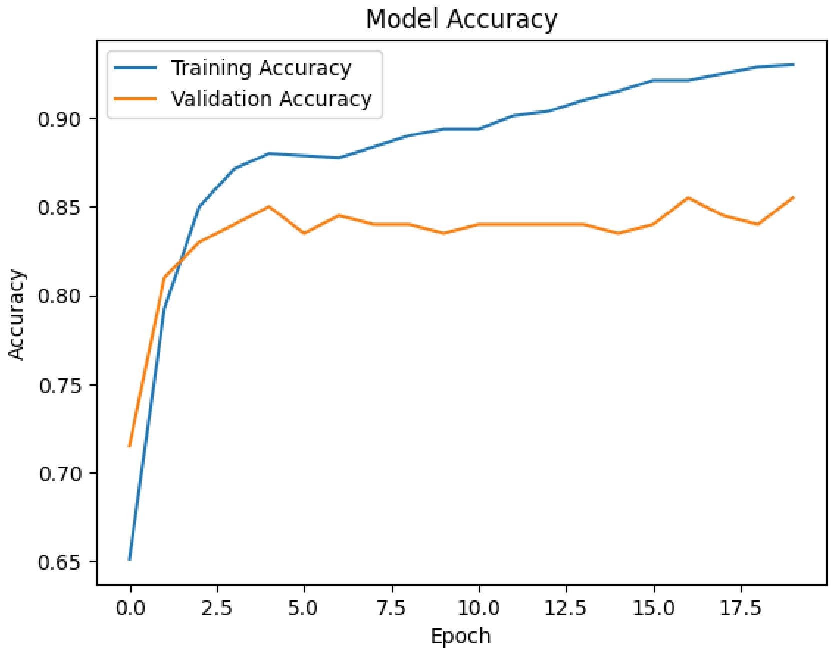


Figure 6: Accuracy analysis

Accuracy indicates the framework's correctness in predicting the BT instances, while the loss quantifies the deviation between the real and the categorized results by the system. The training accuracy estimates the system's effectiveness in learning the patterns differentiating BT types, while the testing accuracy evaluates the system's generalization efficiency over unknown data. Figure 6 illustrates the training and testing accuracy analysis, and it depicts that both train and test accuracy increases over the epoch, which demonstrates its capacity to improve classification at each epoch.

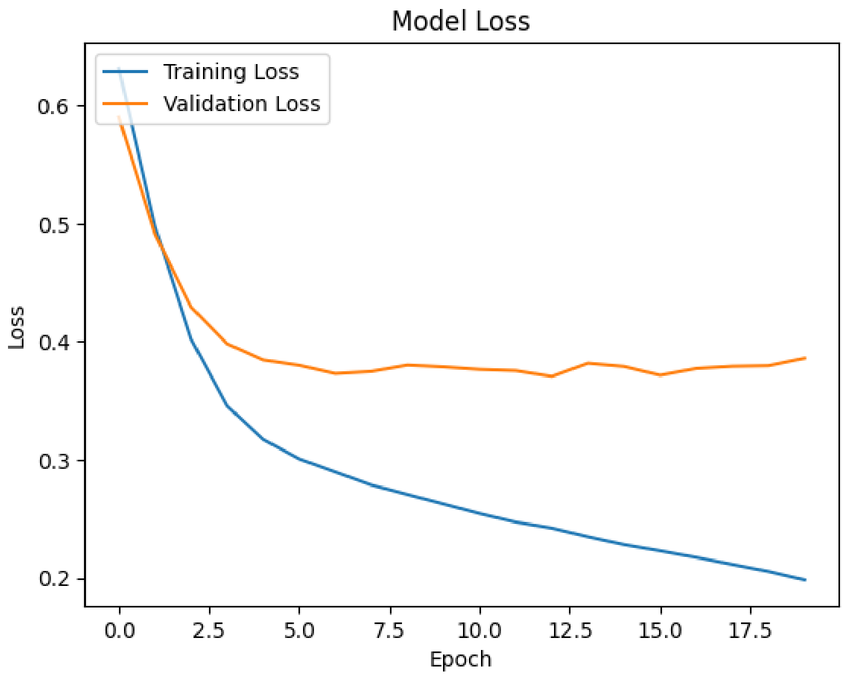


Figure 7: Loss analysis

Similarly, the loss metric was assessed in both the training and testing data. The training loss quantifies the deviation between the actual and classified instances in the train data, while the testing loss indicates the variation between the classified and actual outcomes on the test samples. Figure 7 depicts the loss analysis, with training and testing between 20 epochs and it is observed that the developed framework incurred minimum losses in both train and test phases, illustrating its reliability in understanding the pattern and accurately classifying the BT classes. Here, the developed model has effective learning performance from the training data by the training loss steady decline. however, in few the validation performance has rise according to the overfit training set. Then, new samples of the training data are randomly deactivated to remove the dependence and redundancy.

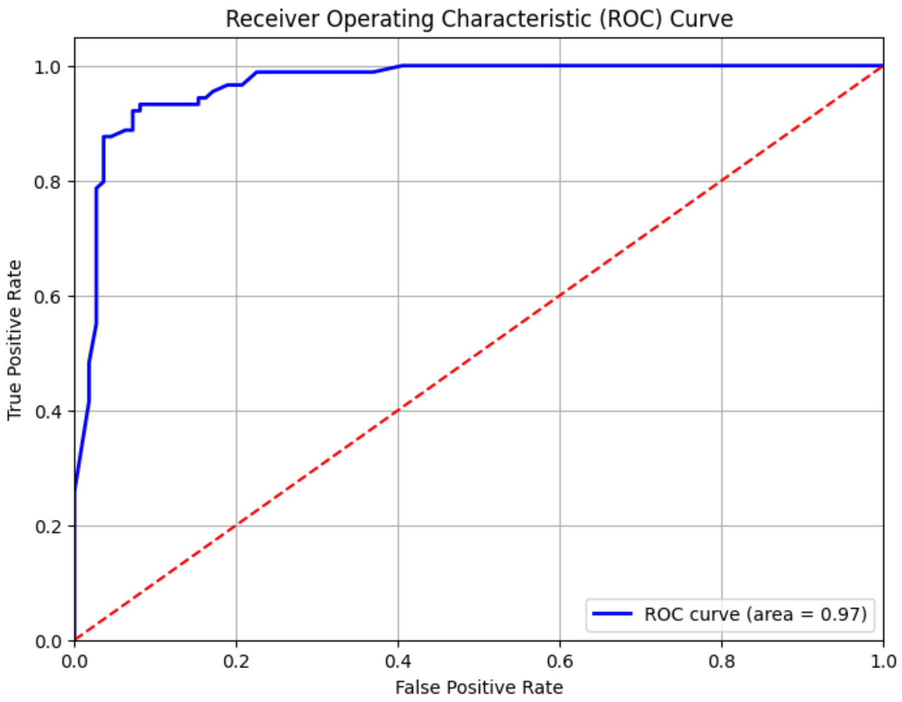


Figure 8: ROC curve

The Receiver Operating Characteristic (ROC) curve denotes the graphical representation used for assessing the model’s classification results across different thresholds. It plots the TP rate and FP rate, measuring the reliability of the model in differentiating positive and negative classes. The higher true positive rate indicates greater performance of the model, while the higher FP rate illustrates its poor performance. The proposed federated learning framework earned an Area Under the Curve (AUC) of 0.97, which is close to 1 highlighting the model’s improved classification performance. Figure 8 presents the ROC curve of the developed algorithm. The performance of a random classifier (AUC = 0.5), which serves as a baseline for comparison. Clearly, the proposed model outperforms random guessing.

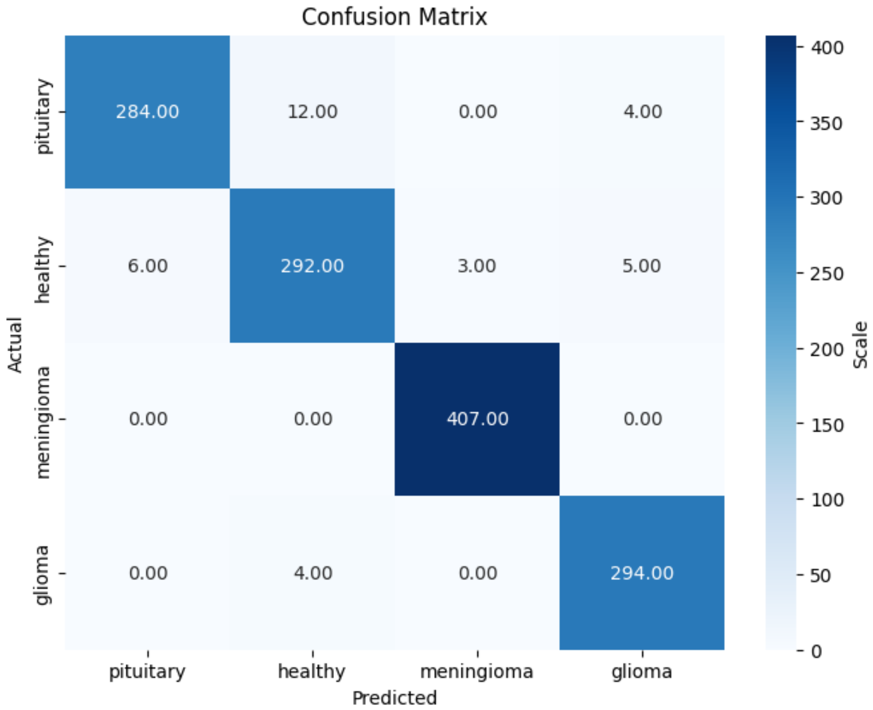


Figure 9: Confusion matrix

The confusion matrix is a tabular illustration used for assessing the performance of the multi-class categorization framework. Figure 9 presents the confusion matrix, which highlights the predicted and actual instances across 4 different classes namely: pituitary, healthy, meningioma, and glioma. The confusion matrix demonstrates number of instances correctly classified and the number of instances misclassified. For example, in the case of the healthy class, the proposed strategy correctly classified 292 instances as "healthy", 6 instances were misclassified as "pituitary", 5 instances were misclassified as "glioma" and 3 instances were incorrectly categorized as "meningioma". The high number of correct classifications signifies the robustness of the model in categorizing different classes of brain tumors.

Performance comparison

The outcomes incurred by the developed model were compared and validated with existing classification models like Convolutional Neural Network (CNN) [33], Decision Making Federated Learning Network (DMFL-Net) [34], Deep Belief with Bidirectional Long-Short-Term Memory (DB-BiLSTM) and Deep Convolutional Spiking Neural Network (DCSNN) [35]. The outcomes of these models are determined using parameters like accuracy, precision, recall, and f-measure. To validate the scalability of the models, their outcomes are estimated at two different data split ratios (80:20 and 70:30).

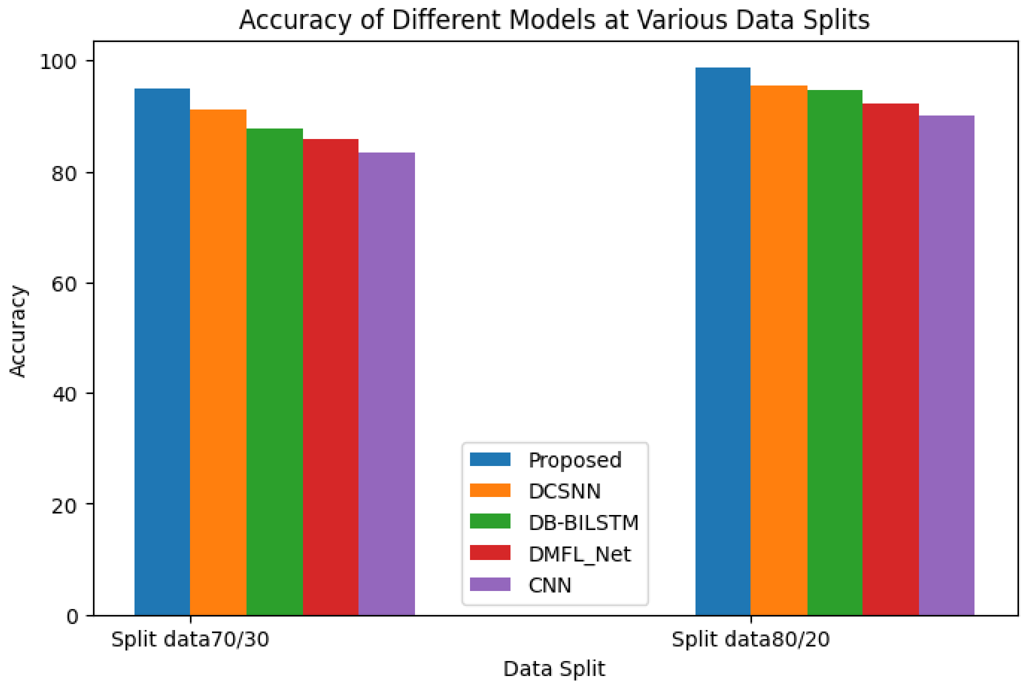


Figure 10: Comparison of accuracy

The comparison of accuracy with the existing approaches is depicted in Figure 10. For the 80:20 data split, the existing models like CNN, DMFL-Net, DB-BILSTM, and DCSNN achieved accuracy rates of 90.12, 92.36, 94.78, and 95.58, respectively, while the proposed strategy obtained relatively higher accuracy of 98.71. On the other hand, for the 70:30 data split, these models obtained accuracy rates of 83.46, 85.91, 87.65, and 91.23, respectively, while the developed approach achieved 94.87. From this evaluation, it is evident that the proposed strategy achieved better accuracy than the conventional models. This manifests that the incorporation of Deep CapsNet into the FL model has ominously increased the model's accuracy in BT classification.

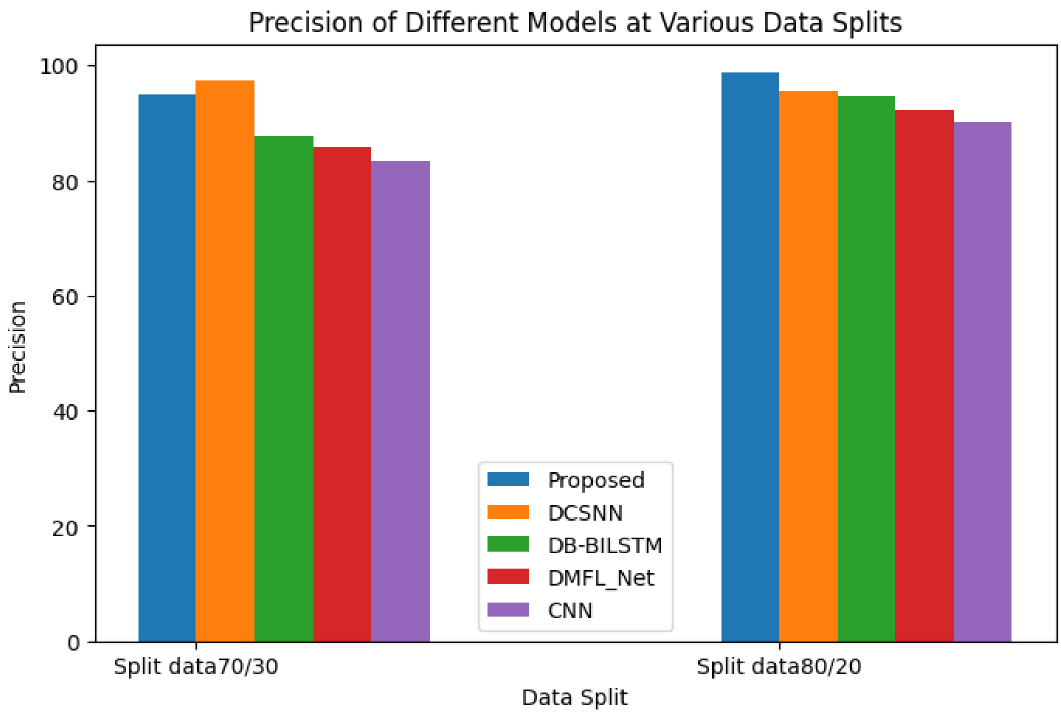


Figure 11: Precision comparison

The assessment of precision with the conventional approaches is depicted in Figure 11. For the 80:20 data split, the conventional models such as CNN, DMFL-Net, DB-BILSTM, and DCSNN obtained precision of 90.13%, 92.37%, 94.79%, and 95.58%, respectively, while for the 70:30 data split, these models earned precision of 83.47%, 85.92%, 87.65, and 91.24%, respectively, while the presented methodology earned precision of 98.70% and 94.88% for 80% and 70% of training samples. The enhancement of the developed algorithm's precision highlights its reliability in detecting the true positive instances compared to existing frameworks.

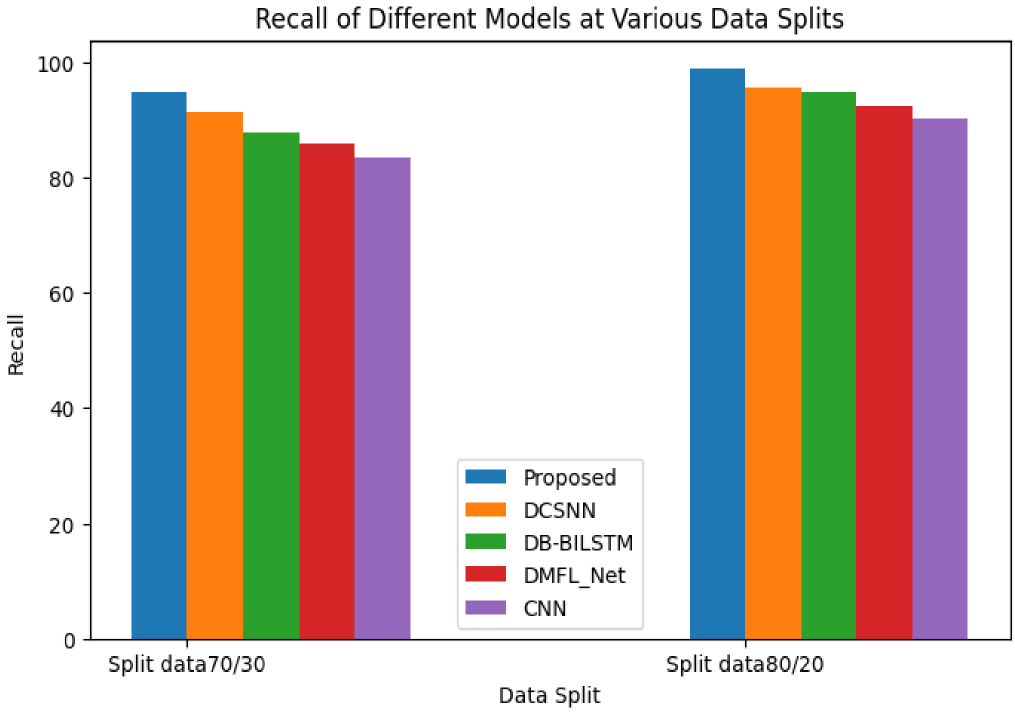


Figure 12: Recall comparison

The comparative assessment of the recall metric is depicted in Figure 12. The recall metric quantifies the model’s reliability in detecting and capturing the relevant patterns crucial for accurate BT classification. For the 80:20 data split, the above-stated existing models such as CNN, DMFL-Net, DB-BILSTM, and DCSNN attained recall of 90.12%, 92.37%, 94.79%, and 95.58%, respectively, while the presented framework attained relatively higher accuracy of 98.71. Similarly, for the 70:30 data split, these approaches obtained recall rates of 83.47%, 85.91%, 87.66%, and 91.24, respectively, while the presented methodology achieved 94.87%. The improvement of recall in the designed algorithm highlights the significance of integrating FL-DCN model. This also demonstrates that compared to the currently available algorithms, the designed strategy precisely tracks and identifies the instances required for accurate BT class prediction.

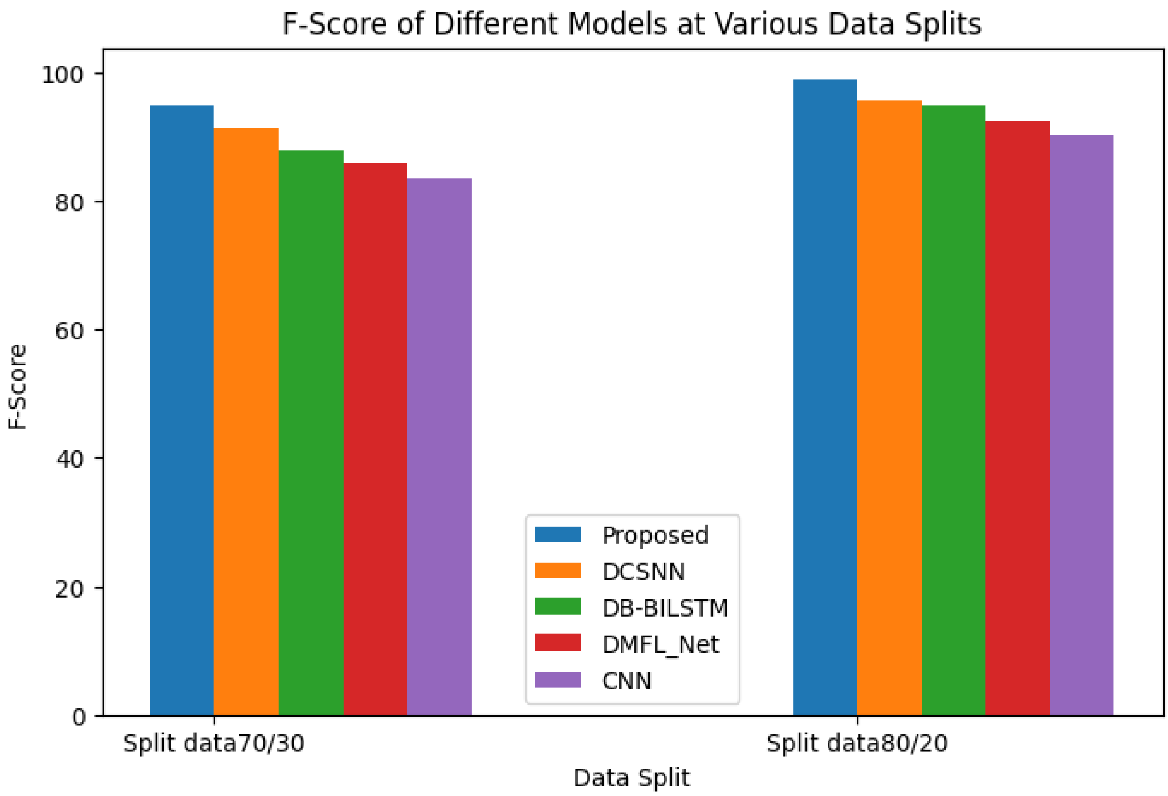


Figure 13: F-score comparison

The comparison of F-score or F-measure is depicted in Figure 13. The assessment of this metric evaluates the capacity of the model to predict and classify both benign and malignant brain tumors. The existing approaches including CNN, DMFL-Net, DB-BILSTM, and DCSNN, and the proposed strategy achieved f-scores of 90.14%, 92.39%, 94.80%, 95.59%, and 98.81%, respectively, for 80% of training data. On the other hand, these methodologies earned f-scores of 83.47%, 85.92%, 87.67%, 91.25%, and 94.89%, respectively for 70% of training data. This comparative study illustrates that the presented approach earned a greater f-score than the conventional algorithms, manifesting its efficiency in providing a balanced classification of brain tumors.

This comparative assessment of the model's performances with the conventional models validates that the designed FL strategy earned improved results than the existing ones in terms of accuracy, precision, recall, and f-measure, highlighting its effectiveness in providing a correct classification of brain tumors.

Discussion

This study designed innovative federated learning-based classifier for precise detection and categorization of BT. Unlike conventional models, this strategy offers decentralized training enabling the system to predict the brain tumor, while preserving data privacy in the e-healthcare applications. The presented work used the Kaggle brain MRI data as an input database, which is then preprocessed by following steps like image resizing, noise removal, and contrast enhancement. Consequently, the U-net algorithm was applied to the preprocessed image for tumor segmentation and feature extraction. The extracted feature sequences from the U-Net were divided into subsets for training the local models in the FL environment. In the FL module, each local model is trained with different feature subsets using the Deep Capsule Network, enabling it to understand the complex and hierarchical patterns significant for tumor classification.

Table 1: Comparative assessment

Model	Accuracy	Precision	Recall	F-score	Training time	Testing time
CNN	86.79	86.80	86.80	86.81	0.23	0.04

DMFL_Net	89.14	89.15	89.14	89.16	0.27	0.068
DB-BILSTM	91.22	91.23	91.22	91.23	0.51	0.06
DCSNN	93.41	93.41	93.41	93.42	0.51	0.05
Proposed	**96.79**	**96.79**	**96.84**	**96.85**	**0.031**	**0.023**

The classification results of the LMs are then combined using the FedAvg and updated into the global model for tumor classification. The presented study was executed in the Python software, and the experimental outcomes are estimated for two different training ratios 80:20 and 70:30. Table 1 tabulates the comparative evaluation of the average performances of various models. The presented technique earned average performances of 96.79% accuracy, 96.79% precision, 96.84% recall, and 96.85% f-score. Finally, a comparative assessment was done with the existing approaches such as CNN, DMFL-Net, DB-BILSTM, and DCSNN, which validated that the presented algorithm achieved better results than others. This enhancement of classification performances in the proposed strategy demonstrates that it can be applied in real-world healthcare applications for the identification and categorization of BTs.

Table.3 **Comparative assessment of datasets**

Techniques	**Datasets**	**Accuracy**	**Precision**	**Recall**	**F-score**
CNN with VGG-16 [36]	Brain MRI dataset	89.2	89	89.51	89.39
CNN [37]	Brain MRI dataset	91.05	90.5	91.2	91
CNN with EfficientNet-B0 [38]	Brain MRI dataset	94.2	93.8	94.7	94.5
Blockchain model [39]	Brain MRI dataset	88	88.2	88.2	88.2
FL [40]	Brain MRI dataset	94.1	92.44	92.11	92.2
Proposed	**Brain MRI dataset**	**96.79**	**96.79**	**96.84**	**96.85**

Conclusion

The present study, develops the efficient brain tumor detection and classic cation framework named as FL-DCN. This model functioned as privacy preserving as well as performance assessment of effective strategy. By integrating the strengthen of CapsNet model with FL network overcome the challenges more effectively. The objective of this research is to offer precise BT classification while ensuring the privacy of the data. The presented strategy was trained and validated using the Brain Tumor data from the Kaggle site, and the implementation outcomes illustrated that it achieved average performances of 96.79% accuracy, 96.79% precision, 96.84% recall, and 96.85% f-score. Furthermore, a comparative study was performed with existing models like CNN, DMFL-Net, DB-BILSTM, and DCSNN, which highlighted that the parameters such as accuracy, precision, recall, and f-measure are enhanced in the designed model by 3.38%, 3.38%, 3.43%, and 3.43%, respectively. These enhanced performances make the developed algorithm reliable for the classification of BT in real-world healthcare scenarios. However, the proposed strategy faces issues like computational overhead and limited scalability. While maintaining the higher performance the developed FL model gas ensures data protection directive proficiently. Hence future work should concentrate on developing a computationally effective FL approach with adaptive features for more reliable performances. Developing the lightweight CapsNet model will enabled to handle the non-IID local data for the layers. Moreover, integration of real-world application may enhance the operational constraints and validate the system performance under clinically acceptable.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

Funding: Not applicable

Conflicts of interest Statement: Not applicable

Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code availability: Not applicable.

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