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RESEARCH ARTICLE

Segmentation Synergy with a Dual U-Net and Federated Learning with CNN-RF Models for Enhanced Brain Tumor Analysis

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Abstract:

Background:

Brain tumours represent a diagnostic challenge, especially in the imaging area, where the differentiation of normal and pathologic tissues should be precise. The use of up-to-date machine learning techniques would be of great help in terms of brain tumor identification accuracy from MRI data.

Objective

This research paper aims to check the efficiency of a federated learning method that joins two classifiers, such as convolutional neural networks (CNNs) and random forests (R.F.F.), with dual U-Net segmentation for federated learning. This procedure benefits the image identification task on preprocessed MRI scan pictures that have already been categorized.

Methods:

In addition to using a variety of datasets, federated learning was utilized to train the CNN-RF model while taking data privacy into account. The processed MRI images with Median, Gaussian, and Wiener filters are used to filter out the noise level and make the feature extraction process easy and efficient. The surgical part used a dual U-Net layout, and the performance assessment was based on precision, recall, F1-score, and accuracy.

Results:

The model achieved excellent classification performance on local datasets as CRPs were high, from 91.28% to 95.52% for macro, micro, and weighted averages. Throughout the process of federated averaging, the collective model outperformed by reaching 97% accuracy compared to those of 99%, which were subjected to different clients. The correctness of how data is used helps the federated averaging method convert individual model insights into a consistent global model while keeping all personal data private.

Conclusion:

The combined structure of the federated learning framework, CNN-RF hybrid model, and dual U-Net segmentation is a robust and privacy-preserving approach for identifying MRI images from brain tumors. The results of the present study exhibited that the technique is promising in improving the quality of brain tumor categorization and provides a pathway for practical utilization in clinical settings.

Keywords: Federated learning, Brain tumor segmentation, MRI analytic synthesis, Neural aggregation diagnostics, Convolutional neural network-(CNN), Random forest (RF).

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1. INTRODUCTION

1.1. Background

Brain tumors pose a significant medical challenge due to their location within the brain and the critical functions they influence. However, their location within the brain and the many crucial ones they direct constitute a considerable medical challenge for brain tumors. The tumors may be categorized into

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two basic groups: primary tumors, which happen in the brain, and secondary tumors, otherwise called metastatic tumors, which are the ones that have drifted to the cerebrum from different body parts. With brain tumors, factors like tumor type, site, size, *etc*., reflect different grades of severity, and at the same time, a lot of differences are to be seen about the treatment choices in the case of such tumors [1]. As it has been shown, early detection of brain tumors is necessary for several reasons. The earlier tumor detection is possible, the more comprehensive the range of therapeutic methods, some of which may be less invasive, have higher efficiency, *etc*.

A brain tumour is a significant medical challenge primarily because it is an intracranial lesion with a significant effect on critical processes. Early identification is crucial since more interventions may be applied, which could be less disruptive and potent. Early diagnosis would also prove helpful in managing the disease and could help slow or halt the progress of cancer cells to enhance the quality of the lives of patients and their expected span. MRI falls under the diagnostic technologies that can be useful in the early detection of tumours. Incorporating the ML algorithms with MRI may significantly enhance the accuracy and reliability of the brain tumor diagnosis. The performance achieved in image analysis and classification tasks in recent times has been quite inspiring, and techniques including transformers, diffusion models, Mamba, and Mega Lodon have been used. Our goal in this project is to enhance the identification of brain tumors from MRI pictures utilizing CNNs other than R. F. F. embedded in the federated learning system. It also includes dual U-Net segmentation based on the criterion of segmentation policy [2].

This strategy leverages all the components to provide reliable and privacy-preserving diagnostics as the guarantee. In LGE-MRI images, the left atrium (LA) is clearly outlined, which aids in diagnosis for medical professionals. It has also a vital role in differentiating and managing diseases related to atrial fibrillation. Precise separation helps in the accurate planning of the treatment, the evaluation of the dangers, and the monitoring of the evolution of the disease. This may lead to precise segmentation of LA that would ultimately improve the precision in therapy targeting, better patient outcomes, and rationalization of therapeutic decisions. Thus, detailed structural representations, such as the left atrium, are vital in procedures like catheter ablation. The timely intervention may have a fantastic impact on improving the prospects, where only through the intervention can the likelihood of tumor proliferation and spread be reduced, and even the quality of life and survival rates continue to change for a change in patients.

This is because the brain is limited in space, with the tumor alluding to the hindrance of critical neurological functions; the management and treatment of these conditions become more complex in their advanced stages [3]. It also suggests that early tumor detection might allow the administration of targeted therapy that damages only cancer cells while sparing neighboring healthy brain tissues.

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1.2. Problem Statement

The brain is a sensitive organ to which changes should not be introduced arbitrarily because minor damage can multiply its adverse effects as a giant functionality loss. Early intervention might help improve symptom management, likely mitigating the damage to the patient's mental, physical, and emotional well-being. The importance of early detection proves the necessity of advancement in existing diagnostic technologies and techniques, including imaging tools like magnetic resonance imaging (MRI), which serves an essential function of cancer detection in the brain [4]. Advances in magnetic resonance imaging (MRI) coupled with machine learning algorithms for image interpretation can enhance the precision, promptness, and effectiveness of brain tumor diagnosis. The FL with convolutional neural networks and R.F.F. classifiers in combination with the seminal dual U-NET solution is a contemporary approach in the domain. In this connection, scientists aim to make brain tumor identification and categorization more rapid and efficient through these technologies, enabling them to receive appropriate treatment promptly.

1.3. Research Objectives

The primary objectives of this study are to:

• This study is in integrative practices and their possible transformation of early brain tumor diagnosis [5]. It specifically focuses on how these methodologies could enhance image analysis through image analysis-based privacy-preserving collaborative learning frameworks. Magnetic resonance imaging (MRI) is a non-invasive procedure essential for detecting and describing brain cancers. Stationary consists of stationary or standing waves (to state the obvious), which occur when two waves of equal frequencies are of different phases and always occur spatially [6].

• Hence, the displacement curve is always different from the superposition of displacements resulting from the motion of two different individual wave pulses, which is always the same. Stationary states are also known as stationary state solutions. By using a strong magnetic field, radio waves, and computer technology, magnetic resonance imaging (MRI) renders intricate brain images and, in general, body regions. It allows MRIs to identify different parts of the brain tissue.

• It ascertains them as a very effective tool in identifying complications in the complicated brain anatomy [7]. The role of MRI in diagnosing brain tumors is multifaceted and crucial. It furnishes crucial data that aid in several essential domains. Given that Tumor Detection: Unlike detecting tumors using high-resolution imaging, MRI uses contrast to highlight the difference between standard and diseased tissue.

• This technology is susceptible and can diagnose even minor cancer cases, making it essential for early detection. Tumor Characterization: MRI helps devise other interventions besides tumor detection by identifying tumor type, benign or malignant. It is also necessary during imaging that different imaging sequences and contrast chemicals are used to determine the component's composition and vascularity, among other critical properties of the tumor that are crucial for accurate diagnosis and strategizing the line of treatment.

Treatment Planning: MRI scans are a valuable aid in improving treatment approaches. They allow evaluation of its dimensions and location relative to adjacent structures, which is essential for treatment planning-surgery, radiation, and others [7].

• The images produced are highly accurate, which has allowed medical practitioners to develop the ability to pinpoint tumors accurately and provide minimal damage to the surrounding brain neuroticizes. Therapeutic Monitoring: MRI monitors tumor volume changes during and after therapy to estimate the treatment response [8]. It serves as a diagnostic instrument by characterizing the effectiveness of the selected therapy; it provides tangible evidence of change in the form of variations in tumor diameters, *etc*. It is a central part of determining the recurrence of the problem and guiding relevant changes in the therapy as required.

• Research and Development: The postulation of MRI imaging in brain tumor treatment options is enabled by ongoing research and is critically important. It aids in the development of new therapies and the understanding of tumor biology. F.L.L. is a novel technique of ML algorithms trained by numerous decentralized computer devices or servers to append retained local data samples that exclude the need for data sharing. These problems include data privacy, security, and access, which are more acute in the healthcare sector. By decentralizing the training data through Federated Learning (F.L.L.), one can ensure compliance with tight data protection regulations, such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA), as information stays in place. The models are brought to the data to be trained rather than to consolidate the figures for training.

1.4. Significance of the Study

• The model of federated learning is trained on data belonging to different individuals, which are distributed in local datasets to several local environments, such as hospitals or research institutions, with individual participants. No lines of code are sent back to the central server; only updates to the model are made in the form of gradients or changes to the parameters. The rationale of this aggregation is to improve the global model, which is afterward provided to all participants who use it for further training [9].

• The learning system is iterative, and this iteration continues until the proposed model attains the desired accuracy and performance. Improved privacy and security: On-premises configuration ensures that Federated Learning reduces the chances of sensitive patient data leaking due to transmission or storage in one centralized database. The confidentiality of data-this feature is crucial in the healthcare sector, where protecting patient confidentiality is paramount. In health care, information from various sources is inaccessible since data is located in disparate ways.

• It is stored in different institutions and locations, which makes access to this data difficult and expensive. It presents a challenge in creating models that can be used across various groups. Federated Learning (F.L.L.) supports the partnership of numerous establishments to train models through different data sets, leading to higher robustness and viability of A.I.I. answers to a broad spectrum of patient and condition demographics. Regulatory Compliance: F.L.L. complies with medical data's legal and ethical use by limiting data transfer and ensuring that personal health information is safe until authorized.

• Enhanced Model Performance: Because it is possible to get information from various datasets to get better and more reliable models, they understand different instances, disease presentations, and responses to treatment options from a broader perspective. This benefit may be even more significant for rare medical diseases or heterogeneous people commonly inadequately represented in centralized databases [10]. It is suitable for federated learning and allows data to be modified in real time. It facilitates the evolution of A.I.I. models suitable for evolving trends in health conditions, novel treatments, and emerging diseases.

• Resource efficiency: F.L.L. could reduce optimum computation effectiveness by dividing the workload across multiple nodes. As an approach, this method enables healthcare companies to leverage their existing designs, diminishing the capital investments needed to acquire centralized processing centers.

1.5. Scope and Limitations

• The challenges faced in Federated Learning in healthcare are that the communication must be reliable, the methods of local data must be of high quality, authentic, and of good quality, there must be the provision of managing variance in data across nodes (non-IID data), and there must be sustainable communication channels for model updates.

• Organizations Additionally, the success of federated learning currently relies on the active participation and contributions of all participating organizations, prohibiting low-efficiency cooperation and providing proper incentives. Federated Learning symbolizes an essential shift in training machine learning models. It enables the utilization of the potential of artificial intelligence in health care, but it also addresses significant privacy, security, and access to data concerns [11].

• In the coming future, as it continues its development, this technology offers unique opportunities for advances in medical research and progress in patient care, allowing for the development of a new level of individualized, customized, anticipatory, and anticipating approach in the field. The domains of artificial intelligence (A.I.I.) and machine learning (ML) have caused a transformative change in medical picture analysis, leading to the development of advanced apparatuses in terms of diagnostic, therapy modulation, and patient monitoring utilities. When processing complex imaging data, designs based on convolutional neural networks (CNN), random forests (R.F.F.), and U-Net should be regarded as remarkable solutions for their effectiveness and efficiency [12].

• These models possess unique strengths during medical imaging, including MRI, CT, and X-ray screening. However, all artificial neural networks, specialized neural networks, named convolutional neural networks (CNNs), are second to none in handling visual data that involves its analysis and interpretation. Artificial neural network architectures utilizing unsupervised learning are very efficient in medical image analysis since they can learn not only spatial hierarchies of characteristics from images but also A CNN consists of different layers, for example, convolutional layers, pooling layers, and fully connected layers [13].

• Support Vector Machine (SVM) is famous for its simplicity and versatility, as it can quickly cope with binary and multi-class classification issues [14]. Random Forest, abbreviated as R.F.F., is a widely implemented technique in medical analysis for feature selection and classification. Structurally, it can cope with high-dimensional data that may come from a medical imaging device and works well with its ability to resist overfitting [15].

• It has been observed that Random Forest (R.F.F.) has been employed in several tasks ranging from illness prediction to organ segmentation and lesion classification [16]. It is widely used as a unit in a pipeline built on preprocessing techniques and other machine-learning models. Often referred to as the U-network architecture, the convolutional neural network designed for effective and accurate picture segmentation is the U-Net [17].

The U-Net design was initially developed to accommodate biological image segmentation. The amalgamation of CNN, R.F.F., and U-Net architectures, along with advanced filtering techniques like Median, Gaussian, and Wiener, helps improve the efficiency of diagnostic and treatment planning tools. Each approach tackles specific issues related to medical imaging data, so the approaches provide distinctive information. Yet when brought together, they offer a comprehensive strategy that capitalizes on the positives of each and significantly enhances how well and what yield is produced [18].

2. LITERATURE REVIEW

2.1. Early Detection And Deep Learning Algorithms

The study presents a new approach to early detection and time-appropriate treatment guided by a structure of complex deep learning algorithms that serve as the basis for the advanced indicator with the potential to eliminate tumor development in less than 1% of the population with inherited mutations. The research now provides a coagulopathies CNN architecture consisting of sophisticated algorithms for automatically classifying brain images into four groups. As an extra, a U-Net model is presented for correct brain tumor segregation from MRI images. The goal is to advance patient outcomes by detecting brain tumors before they start causing dreadful effects. C.T.T. has been evaluated on six segmented datasets through an in-depth analysis of segmentation’s impact on brain MRI images’ tumor classification accuracy [19]. The evaluation of two classification techniques and performance measures, including accuracy, recall, Precision, and AUC, showed that newly constructed deep learning-based models outperform the present pre-trained models in all aspects. The classification model showed a remarkable accuracy of 98.7% when applied to a merged dataset and 98.8% when combined with the segmentation method, once again drawing attention to the seeding effect of segmentation. Similarly, the four separate datasets attained a maximum classification accuracy of 97.7%. During automatic diagnosis and segmentation of brain tumors using the proposed framework, the results underscore its effectiveness for finding proper tumor contours, thus implying its clinical application value to help the process of diagnostics based on MRI scans.

2.2. Classification Techniques and Performance Measures

The potential for fatal brain tumors necessitates timely diagnosis, emphasizing the importance of early detection as it could prevent loss of Life. This urgency has led to the development of a categorization process specifically designed for a swift and accurate diagnosis to avoid unwanted consequences. This study utilized a sophisticated Convolutional Neural Network (CNN) model. This model categorizes brain magnetic resonance images (MRIs) into four distinct groups: meningioma, glioma, no tumor, and pituitary tumor. It does so by analyzing the unique features of each image and assigning it to the group it most closely resembles. In addition to classification, a U-Net-based automated segmentation model was built to segment tumor sections from brain MRIs precisely. This model addresses the problem of heterogeneity stemming from the distinct locations, morphology, and structures of tumors. The focus of this study is to ascertain the performance of automated tumor segmentation and its impact on the classification process. The segmentation technique was found to have no significant difference in tumor phenotype classification accuracy compared to other non-segmentation strategies. However, it's important to note that the absence of segmentation reduced the classification duration. This presents a trade-off: while segmentation can enhance the Precision of tumor identification, it can also increase the time required for classification. This trade-off may be more or less significant, depending on the specific circumstances and requirements of the case [19].

2.3. Automated Diagnosis and Segmentation

The research also explores the effect of dataset augmentation on a model and its importance in ensuring accurate model prediction. It is evaluated because the research team assesses the classification model in the experiment process on different datasets and compares it to five pre-trained ones. Among the results obtained, the proposed model outperforms these pre-trained models and goes beyond the state-of-the-art approaches presented in the literature. The segmentation model performed excellently by having all the segmented masks in absolute Precision from every MRI image taken from different datasets, highlighting its stability and accuracy. Due to the study's data results, the implemented automated classification and segmentation models have shown significant progress in recognizing and analyzing early-stage brain tumors [20].

2.4. Dataset Augmentation and Model Prediction

However, the study also points to the insufficiency of a large enough dataset of real-life MRI to provide for more precise accuracy of tumor segmentation and suitable training of the models. To focus on this, the suggested method demonstrates an ability to perform in clinical settings provided that the models are improved considering broader and more varied data sources [4]. This overview presents a research proposal that leverages a supervised CNN Deep Net classifier's unique capabilities for detecting, classifying, and diagnosing meningioma, the most prevalent primary brain tumor in adults. The study employs a deep learning strategy with a methodology that includes preprocessing, categorizing, and segregating, aiming to detect and assess tumor images accurately.

2.5. CNN Deep Net Classifier for Brain Tumors

The CNN Deep Net classifier stands out for its ability to self-recognize distinctive details from superior images and effectively differentiate between normal and pathological (tumor) images. The tumor region is meticulously segmented using a combination of global thresholding and an area-dependent morphology function. This ensures the preservation of spatial invariance and convenience throughout the process. The detected tumors are then classified based on severity by the classifier, which denotes benign (low grade) and malignant (high grade) cancers using the feature properties of the tumors. The proposed approach is evaluated quantitatively and qualitatively, with performance metrics including sensitivity, specificity, accuracy, Dice similarity coefficient, Precision, and F-score. The segmentation accuracy demonstrated by the proposed classifier is remarkable, achieving 99.4% and 99.5% accuracy compared to ground truth images. This significant performance difference underscores the potential of the proposed CNN Deep Net classification system, equipped with a grading mechanism, to enhance the recognition, typing, and classification of meningioma brain tumors in clinical practice [21].

2.6. Model Configuration and Feature Extraction

The model for recognizing and dividing brain tumors is a self-governing model, which this research describes. The model has been configured to eliminate the necessity of human interference through the automated detection and categorization processes, and the clinicians receive enough help [22]. It first performs image filtering algorithms and intensity normalization on the collected images. The next step is to acquire patches to produce images containing extracted patches. In more technical terms, the model computes feature extraction through the grayscale transformation and the colormap process into the binary images of RGB pictures [23]. These binary images are further enhanced by the Local Binary Patterns (LBP) technique, a method used for texture classification. The Convolutional Neural Network (CNN) is employed for feature extraction, leveraging its deep learning capabilities, and is widely recognized in various engineering disciplines. Object detection in identifying brain tumors is done in the model with a machine learning-supported vector machine (ML-SVM), showcasing the innovative approach to object detection methodology used in this model. This model's structural or categorization component is crucial for determining the presence or absence of brain tumors, potentially revolutionizing medical diagnostics [24].

2.7. Comparison of Segmentation Approaches

This research provides a detailed model analysis, comparing it with other available approaches using key metrics such as the Dice Similarity Coefficient, Jaccard Similarity Index, sensitivity, accuracy, specificity, and Precision. The goal is to demonstrate the superior effectiveness and efficiency of the proposed approach to segmenting and detecting brain tumors, providing compelling evidence for its potential value in the medical field [25]. This study suggests a new approach to the most accurate way of grading brain tumors that exploits the volumetric 3D MRI sequence. This technique is also essential to helping the neuroradiologist make a clinical diagnosis. Glioma brain tumors must be classified into two types: low-grade gliomas (LGG) and high-grade gliomas (HGG), and this study is an attempt to employ a deep multi-scale three-dimensional convolutional neural network (3D CNN) architecture in the classification process. The network operates on the whole volumetric T1-Gado MRI sequence. The proposed 3D CNN architecture uses a 3D convolutional layer, and a deep network uses small kernels. This enables it to effectively incorporate local and global contextual information and limit computation weights [26].

2.8. 3D CNN Architecture for Glioma Classification

To begin with, the authors have introduced an algorithm for preprocessing MRI data for data heterogeneity-the natural peculiarity of MRI images based on intensity normalization and adaptive contrast enhancement. In addition, a data augmentation mechanism was employed to improve the training of the deep 3D network. An elaborate study was undertaken to determine the effect of permutation and augmentation processes on classification accuracy. The quantitative evaluations of the Brats-2018 benchmark reveal that the proposed 3D CNN architecture outperforms its 2D CNN counterparts and the current state-of-the-art in differentiating between low-grade and high-grade gliomas. The presented methodology showed an outstanding overall accuracy of 96.49% for the validation dataset, thereby showing the strength of the proper MRI preprocessing technique, alongside the employment of data augmentation that was utilized by efficiently garnering the likelihood and production of valid CNN-based solutions for proficient classification of glioma tumors at the sleeping brain. This work also validates the proposed deep learning framework's effectiveness, especially its preprocessing and augmentation methods, in eliminating the prediction bottlenecks in medical image analysis for automated brain tumor grading progress [27].

2.9. HCNN Classifier for Meningioma Identification

This article introduces a novel HCNN classifier designed to successfully classify imaging data corresponding to brain pictures in a practical way, which facilitates identifying meningioma. The HCNN classifier is based on the Ridgelet, which uses the transform of brain images to decompose and lines the pixel intensity characteristics from the extracted coefficients for training and classification. The results obtained with this novel method have been awe-inspiring, even on long datasets [28]. For BRATS 2019, the HCNN-based meningioma identification method achieved a sensitivity, specificity, and segmentation accuracy of 99.31%, 99.37%, and 99.24%, respectively [29, 30].

2.10. Enhancing MRI for Brain Tumor Diagnosis

This overview discusses the research work that uses deep learning to enhance cancer magnetic resonance imaging (MRI) to facilitate brain tumor diagnosis [31]. MRI scans are crucial in diagnosing brain tumors because they are defined by their proliferation without control. They assist in classifying tumors as benign (noncancerous) or malignant (cancerous). Malignant tumors are the ones with very high mortality, and early identification can drastically reduce such death rates. However, brain tumor classification is one of the most significant challenges due to the clinical and radiological similarities of these tumor classifications. The research sought to categorize MRI pictures into three tumor types precisely: This attempt has been made by a collaboration of meningioma, glioma, and pituitary tumors, as well as the images of healthy individuals and the sagittal, coronal, and axial views, to help radiologists through this tedious task [32].

2.11. Automated Brain Tumor Detection

A composite model that combines many classifiers while taking advantage of features assessed by a convolutional neural network was also used as a methodology. Furthermore, the study investigated the effect of data augmentation and visual quality as measured by image resolution on classification precision, striving for the highest level of Precision. The research sample adopted a CNN structure in addition to several pre-trained models that have been used [33]. It concluded that the ResNet 18 model enables the highest classification accuracy of 95.7%. The finding shows the potential to improve the accuracy of brain tumor classification from the MRI images using robust CNN models allied with suitable data processing approaches. This may help radiologists make better prognoses, which could lead to earlier cancer detection and commencement of successful treatment [34]. The research concerns the complex and critical task of automated identification of brain tumors and the relevant characteristics of tumors, such as location, size, pathologic/component makeup, and distinguishing pathological from normal brain tissue [34].

3. MATERIALS AND METHODS

The methodology portion of a study article that concentrates on MRI datasets for brain tumor identification encompasses many crucial stages: data collection, preprocessing, and augmentation. All these processes are equally important in safeguarding the quality and reliability of the data used for training and validating the proposed machine learning models, as shown in Fig. (**1**).

3.1. Data Collection, Pre-processing and Augmentation

The data collection method includes acquiring MRI images from many sources to build a complete dataset for research involving identifying and analyzing brain tumors. Most MRI datasets, like BRATS (Brain Tumor Segmentation Dataset) (https://www.kaggle.com/datasets/awsaf49/brats2020-training-data), ISLES (Ischemic Stroke Lesion Segmentation), and more, which are publicly accessible or acquired through collaborations with hospitals, are being used. These data sets generally have photos of different tumor occurrences, kinds, and severity levels. It makes them a valuable resource for training and testing machine learning models. The datasets may further comprise the metadata, for example, patient demographics, tumor grade, and other clinical information, which could be crucial for a detailed study. Preprocessing should be performed after the data are collected so the MRI images are ready for analysis. The stage covers multiple subprocesses that enhance the image quality and make it consistent throughout the dataset. Typical preprocessing methods encompass normalization, converting the data values to a standard range, and ensuring conformity in model training. Skull-stripping involves removing non-brain tissues from MRI scans and concentrating on the brain tissue and pathology. Bias Field Correction is a method utilized to correct the intensity inhomogeneity observed in MRI images, thus reducing the differences in brightness and contrast across various photos. Resizing and resampling mean changing images' size and resolution to ensure homogeneity in the dataset. That is especially relevant for batch processing in neural networks that work well.

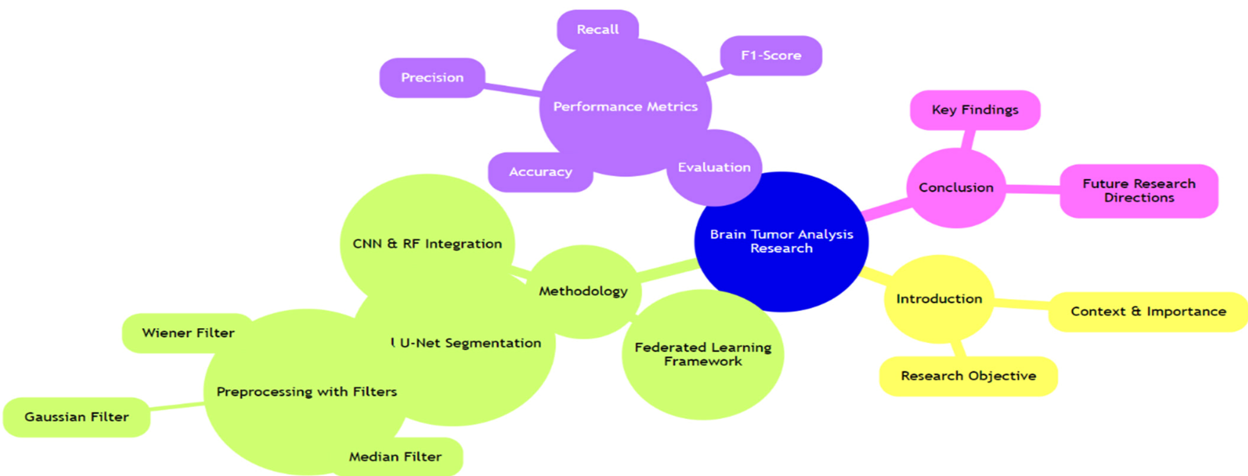

Fig. (1). Methodology for the brain tumor.

In this Fig. (**2**), images from the BRATS2020 Training dataset, available on Kaggle (https://www.kaggle.com/datasets /awsaf49/brats2020-training-data), have been used for research work.

Data augmentation is an approach that is employed to synthetically enlarge a dataset by creating modified copies of the presented images. This is particularly useful in medical image analysis since similar amounts of data may be challenging to find. Augmentation techniques include a variety of methods. For example, she came by and brought us a lovely cake. Rotation: rotation of the pictures at different angles to mimic several orientations. Flipping: Transforming the images regarding the orientation to make the dataset richer in diversity. Zooming is changing the size of photographs, for instance, zooming in or zooming out, when emulating the sizes of areas of interest. Elastic deformation concerns change that mimics the natural variability seen in human anatomy.

3.2. MRI Image Pre-processing: Techniques for Noise Reduction and Feature Strengthening

Preprocessing images is an essential stage in magnetic resonance imaging research that aims to suppress noise and bring out features to increase the accuracy of future image segmentation and classification. Among these, median, Gaussian, and Wiener filters are three commonly used filtering methods for improving picture quality, each with its methodology for enhancing image quality, as shown in Fig. (**2**). The method of adding noise to the MRI data at first and eliminating it at a later stage is applied because it helps to enhance the learning capability and the performance and robustness of the model for realizing various application contexts. This way, noise enhances the model’s capacity to identify and focus on significant aspects of the pictures, reducing its sensitivity to noise and subtle changes in the data. This helps mimic real-life scenarios where medical pictures may have different noises due to different acquisition conditions or apparatus. After the desired input is processed and the model is designed to work with noisy data, the picture undergoes denoising. This leads to max segmentations and, hence, accurate analysis. This method enhances not only the model’s loss of clean data but also the ability of the model to learn how to address noisy pictures effectively and increase the overall relevance of the model in clinical practice.

In this Fig. (**3**), the input images has been taken from the BRATS2020 Training dataset of Kaggle (https://www.kag gle.com/datasets/awsaf49/brats2020-training-data).

3.2.1. Median Filtering

The median filter is a non-linear technique employed to remove noise from pictures while maintaining the sharpness of the edges. The algorithm's operation is done sequentially by traversing the image, analyzing each pixel, and replacing its value with a median value from the surrounding pixel. The neighborhood size is predetermined by a fixed sliding window sliding over the image. This method excellently removes “salt-and-pepper” noise, causing virtually no blurring of the images, making it highly useful for MRI images where edge preservation is necessary for accurate tumor diagnosis. Median filtering is a potent tool for removing salt-and-pepper noise without blurring edges. The original pixel value is replaced with the median value obtained from a given window of the nearby pixels for each of the pixels (Eq. **1**).

$$I_{Filtered}\,(x,y) = median\,\{\,I(x+k, y+l)\} \qquad (1)$$

Where $I_{Filtered}$. The filtered image is the original image, and the neighborhood of each pixel(x,y) is defined by the window with offsets *k* and *l*, which range over the size of the filtering window, as shown in Fig. (**3**).

3.2.2. Gaussian Filtering

Gaussian filtering is a linear process that involves convolving the image with a Gaussian function. This filter smooths the image by computing an average of neighboring pixel values. Each pixel's influence is determined by its distance from the center pixel, whereby closer pixels have a more significant impact. The pixel weights obey the normal distribution. Thus, the pixels far from the central pixel have less effect on the outcome. The degree of smoothing is controlled by the Gaussian function's standard deviation (σ). Gaussian filtering is the best method to remove the image's noise and slight intensity variations. Nevertheless, it also introduces a blurring effect that might make the little yet essential features critical for medical diagnosis less conspicuous (Eq. **2**).

$$G(x,y) = \frac{1}{2\pi\sigma^2}\, e^{\frac{-x^2+y^2}{2\sigma^2}} \qquad (2)$$

Where $G(x,y)$ is the Gaussian function, σ is the standard deviation of the Gaussian distribution, and x and y are distances from the central pixel. The filtered image is obtained by combining this Gaussian function with the original image,

Where I_{filtered} is the filtered image, *I* is the original image, and *G* is the Gaussian kernel, as shown in Fig. (**4**).

In this Fig. (**4**), the input images has been taken from the BRATS2020 Training dataset of Kaggle (https://www.kag gle.com/datasets/awsaf49/brats2020-training-data).

3.2.3. Wiener Filtering

Wiener filtering is an adaptive approach to minimize the mean square error between the output of the filter and the desired.

Image. It considers the aging process and additional noise, making it highly efficient where noise properties are known or can be anticipated. Wiener filtering in M.R.R. images smoothest different regions by considering local pixel variance. This strategy retains the fainter details in areas of more variation, such as edges, and over smooth uniform regions with more robust smoothing. Wiener filtering is an appropriate approach for enhancing MRI images as it can reduce noise, leaving the essential characteristics for analysis intact (Eq. **3**).

$$H(u,v) = \frac{S_{xx}(u,v)}{S_{xx}(u,v) + S_{nn}(u,v)} \qquad (3)$$

Where H (u, v) is the Wiener filter in the frequency domain, S_{xx} (u, v) is the power spectrum of the original image, and S_{nn} (u, v) is the power spectrum of the noise. The filtered image is then obtained by applying the inverse Fourier transform to the product of the Wiener filter and the Fourier transform of the noisy image (Eq. **4**).

$$I_{Filtered} = F^{-1}\{H(u,v).F\{I_{noisy}\}\} \tag{4}$$

Where F and F−1 denote the Fourier transform and the inverse Fourier transform, respectively, and *I* noisy is the noisy image.

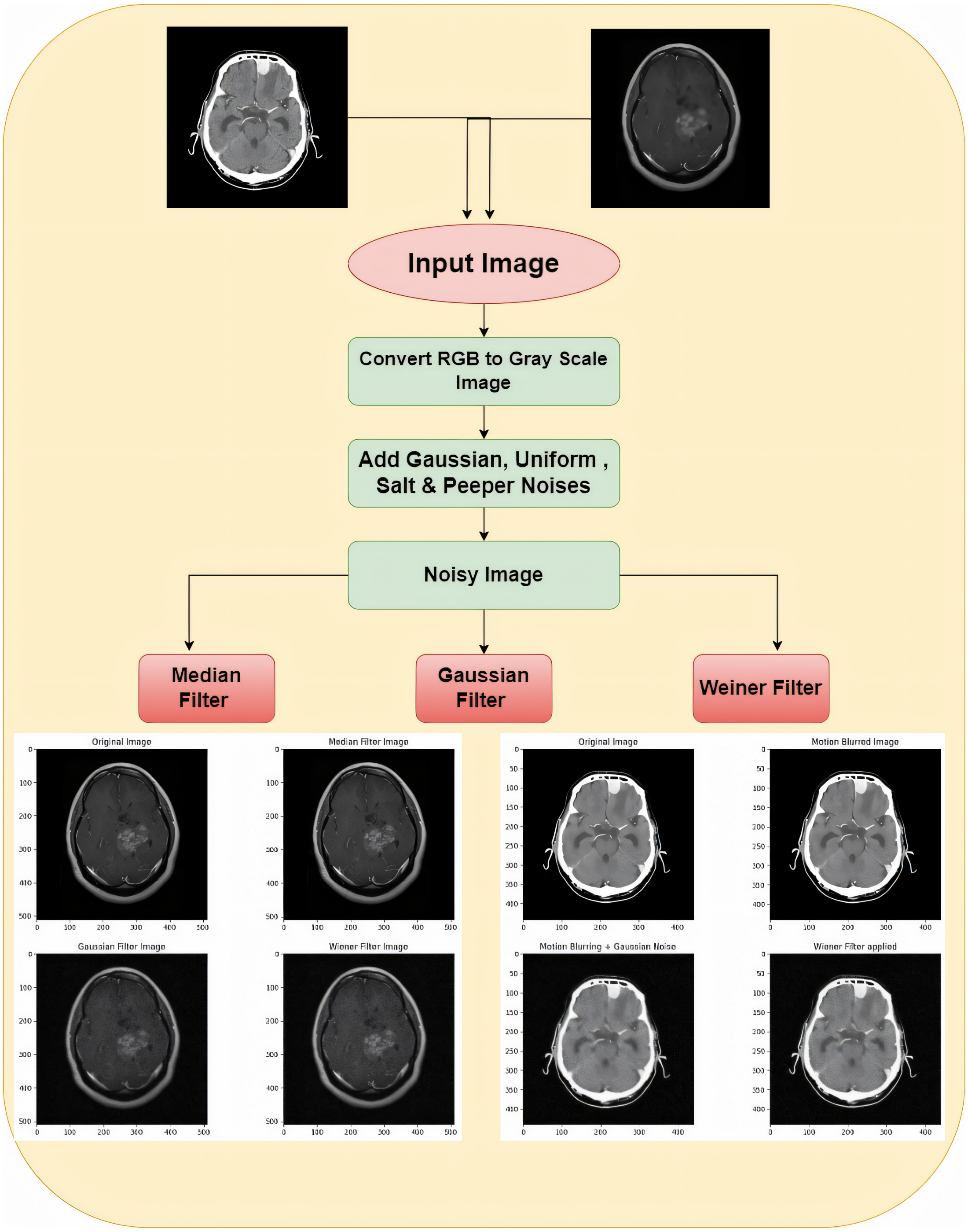

Fig. (2). Filtering techniques in input MRI images.

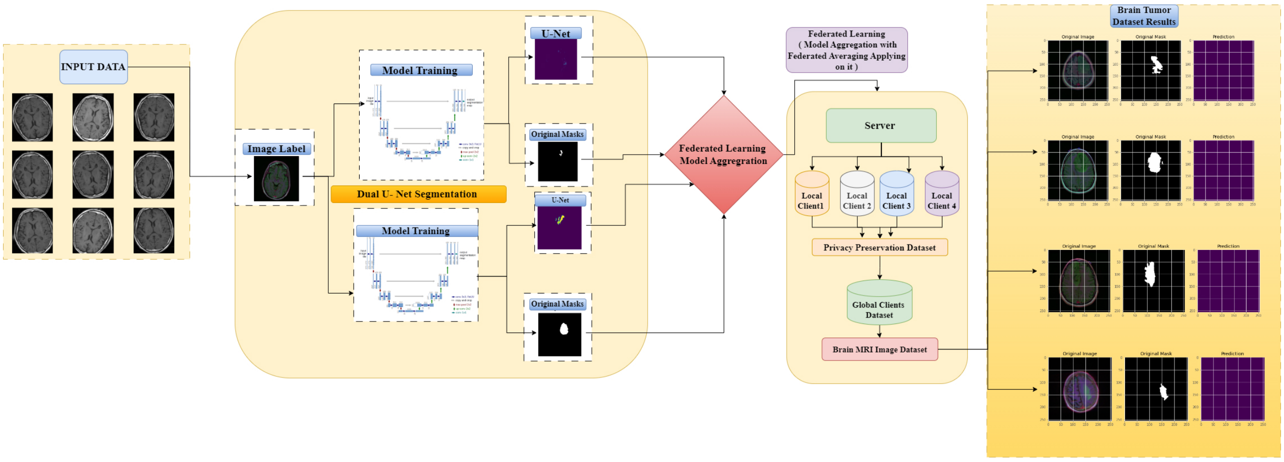

Fig. (3). Dual U-Net architecture with federated learning framework in input MRI images.

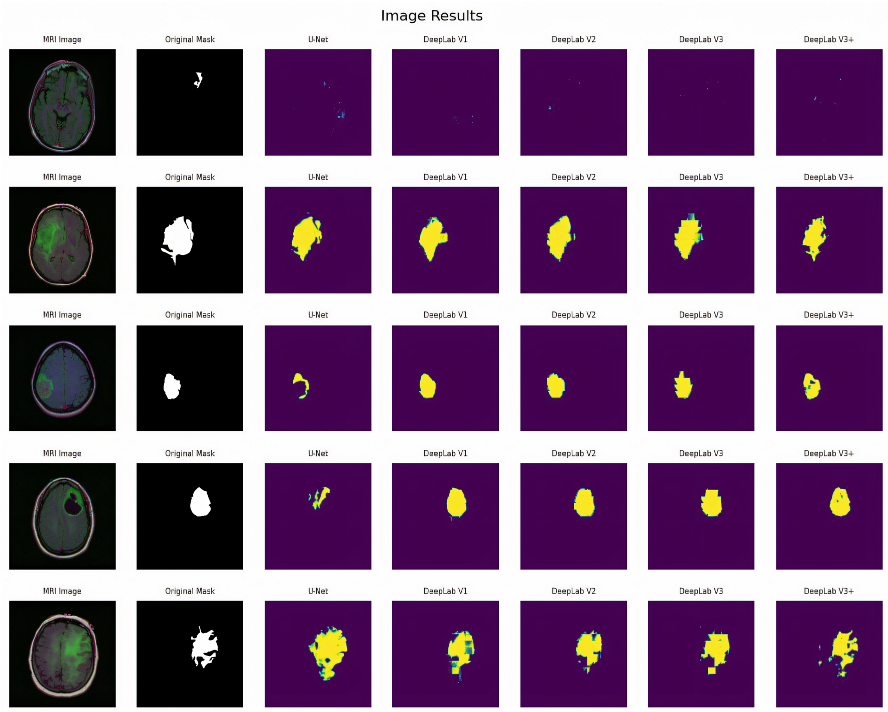

Fig. (4). Segmentation results techniques in input MRI images.

3.3. Utilization of MRI Image Pre-processing

The filtering techniques are used during the processing of MRI images to achieve some objectives. Median filtering is employed to eliminate abrupt noise artifacts but retains the borders of the brain or malignancies, thus ensuring the preservation of vital boundaries. Gaussian filtering is commonly used to achieve picture smoothing, thereby suppressing high-frequency noise, which can sometimes conceal minor differences in tissue properties.

By selecting the σ value, one can effectively control the smoothing degree to find an optimal level of trade-off between reducing noise and preserving the details. The adaptive capability of Wiener filtering renders it most suitable for MRI images depicting spatially varying noise patterns. Local content-based filtering adjustments may significantly improve the visualization of some areas of interest, *e.g.*, tumor regions. Each filtering method can be selectively performed depending on the attributes of the MRI data and the particular needs of the analytics work. Here, the type of noise present and the importance of maintaining precise features are factors. These filters can be integrated into a preprocessing pipeline, improving the quality of inRI images and allowing more accurate and reliable identification and categorization of brain tumors. The dual U-Net structure is an advanced version of the classical U-Net model developed for precisely segmenting complex structures like brain tumors from MRI scans. This architecture effectively captures high-level features and fine details using two parallel U-Net structures. The rest of the sections will discuss the architecture, training process, and implementation for brain tumor segmentation, together with equations and formulas.

3.4. Dual U-Net Architecture with Federated Learning Framework

The original U-Net architecture is a convolutional neural network (CNN) developed for semantic segmentation of biomedical images consisting of a contracting path to capture context and an expanding symmetric path that provides accurate localization. Incorporating two U-Nets in parallel into a Dual U-Net improves feature extraction and segmentation capabilities. Each U-Net consists of A contracting (down sampling) path: Convolution layers followed by max pooling layers to get the image context. The convolution operation can be represented as this T.V.V. being (Eq. **5**).

An LCD one.

$$I_{conv} = ReLU(W * I + b) \quad (5)$$

Where I_{conv} It is the output of the convolutional layer, W represents the weights of the convolutional filter, I is the input image or feature map, b is the bias, and * denotes the convolution operation. ReLU (Rectified Linear Unit) introduces non-linearity. An expanding (Upsampling) path: Transposed convolutional layers that increase the output feature map's resolution to restore an image's details and dimensions for accurate segmentation. The Upsampling operation can mathematically represent ordering a pair of pants instead of a sweater (Eq. **6**).

$$I_{unsampled} = W^T * I \quad (6)$$

Where $I_{unsampled}$ Is the upsampled feature map, W^T Represents the weights of the transposed convolutional filter, and I is the input feature map.

The Dual U-Net architecture merges the outputs of the two parallel U-Nets by employing feature fusion techniques, thus precisely improving the model's capability of segmenting complex features, *e.g.*, brain tumors, as shown in Fig. (**5**).

3.5. Training Process

The loss function, which measures the difference between the predicted segmentation and the ground truth, is optimized to train Dual U-Net. The dice coefficient is a widespread loss function that is widely used for segmentation tasks, and in the case of imbalanced datasets, it works well. The Dice loss is defined as Drinking several glasses of wine, which will make you feel euphoric and happy and drive you to nonsensical chatter (Eq. **7**).

$$Dice\ Loss = 1 - \frac{2\sum p_i g_i + \epsilon}{\sum p_i^2 + \sum g_i^2 + \epsilon} \quad (7)$$

Where pi and gi are the predicted and ground truth values of the pixels, respectively, N is the total number of pixels, and ϵ is a small constant to avoid division by zero.

Where pi and gi are the predicted and ground truth values of the pixels, respectively, N is the total number of pixels, and ϵ is a small constant to avoid division by zero. The model parameters are updated during training to minimize the dice loss, guaranteeing that the predicted segmentation closely matches the ground truth brain tumor segmentation. In this Fig. (**5**), the input images has been taken from the BRATS2020 Training dataset of Kaggle (https://www.kaggle.com/datasets/awsaf49/brats2020-training-data).

In the case of dual U-Net, one U-Net in the dual structure enhances the other's outcome for a more enhanced segmentation precision. The first U-Net, commonly called the contracting path, tries to obtain the global context of the images by down-sampling the input images and obtaining approximate features *via* a series of convolutional and pooling layers. This helps in knowing the general makeup of the picture. The second part of the U-Net, named the expanding route, aims to increase the resolution of the features to provide

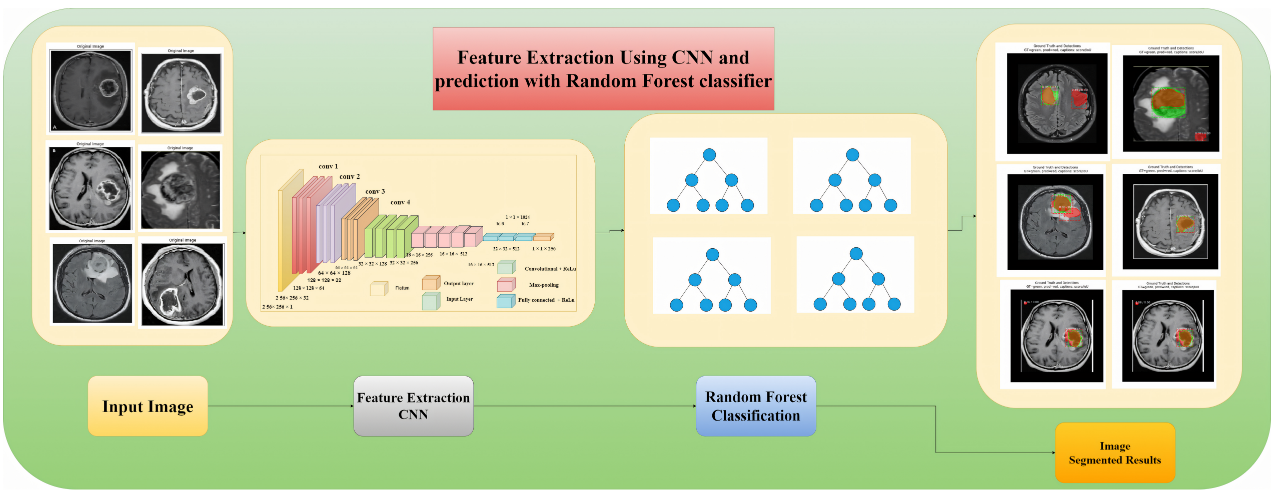

Fig. (5). A federated learning proposed model with CNN RF in input MRI images.

better segmentation details. This is performed by the end-to-end connection of the high-level data from the contracting path with the local features through skip connections. The employment of the global context and the local descriptions ensures that the dual U-Net framework can draw sharp boundaries of complicated structures in MRI images, such as the left atrium and the form of the U-Net structure. Regarding the federated learning structure, the dual U-Net and Random Forest training is decentralized. This means the data is uploaded to each client's device, thus ensuring data protection and meeting the legislation requirement. First, a global model is produced and disseminated to all clients who participate in the survey. After that, each client continues to fine-tune the dual U-Net model by using the local data set to adjust the model weights based on the characteristics of the client's own data set. The local alterations are transferred back to a center server and processed through procedures like Federated Averaging to update the global model. After that, this detailed global model is shipped to all clients for additional refinement for the local implementation. In the same way, in the case of Random Forest, every client trains a local version of the model on their client-server data set. The decision trees developed locally are then combined in the central server to establish a stronger Random Forest Model Globally. Such an iterative process is performed until the quality of the obtained models is satisfactory. However, the method preserves the data anonymity and incorporates different data sources; simultaneously, it introduces further complications into the training process and requires careful synchronization and organization between clients and the central server.

3.6. Segmentation For Brain Tumor Adaptation

The Dual U-Net model provides a suitable solution for brain tumor segmentation owing to its increased ability to consider contextual information and fine details. This is necessary to divide tumors of the brain accordingly, which vary widely in size, shape, and location. The following considerations are typically made to adapt the Dual U-Net for brain tumor segmentation: You can praise yourself for artificial intelligence. Although the preprocessing steps, including normalization and skull stripping, are taken care of on the MRI images, they are done to maintain consistent data quality. Data enhancement approaches such as rotation, flipping, and scaling increase the diversity of training data, thereby enhancing the model's robustness and generalization capability. The model is trained on annotated MRI images; in these images, the mask specifies that tumors exist much more significantly and that boundaries are outlined. Post-processing steps, such as morphological operations, can be applied to the predicted segmentation maps to make the final output more accurate. The ability of a Dual U-Net to efficiently combine features from two parallel networks makes it a potent tool for precisely segmenting brain tumors from MRI images, thus greatly facilitating the diagnosis and treatment planning process. Federated learning is a machine learning situation where the model is to be trained on multiple decentralized devices or servers, but this is done without sharing their local data. The method is highly advantageous when data privacy, security, and access matter most, like in healthcare. The FL setup includes several essential components and processes, such as data distribution, model training, and aggregation methods, elaborated below. In federated learning, the data remains divided among the participating nodes; each could be a device like a smartphone or an organization, say a hospital, with its unique local dataset. These datasets are not transferred or shared but are used for computations locally. The key characteristics include Local Data Stays Private: Each participant's data remains on their device; therefore, privacy and security are guaranteed. Heterogeneous Data: At different nodes, the data can be non-IID (independently and identically distributed), which means that distributions of data can vary significantly from one node to another, which makes training of models challenging. Figs. (**3** and **5**) represent the phases and some of the elements of the holistic segmentation framework. Fig. (**3**) usually means the preprocessing and the first accomplishment of feature extraction by the dual U-Net architecture. This step focuses on creating slices of the MRI images to optimize the borders of the structures of interest, such as the left atrium. This is attained through the proper assessment of general and specific attributes. As for how the two segmentation outcomes determined by the dual U-Net are incorporated to focus on more classification processes using models like the Random Forest, Fig. (**5**) suggests that the segmented areas are further categorized and improved using these methodologies. To connect both models, the output containing segmented regions produced by the dual U-Net from Fig. (**3**) is used as the input for the following classification model in Fig. (**5**). The first segmentation process uses the dual U-Net algorithm, where the masks created are accurate and superior to those made by the base U-Net algorithm. They are then utilized by what is depicted in Fig. (**5**), for instance, the Random Forest model or other classifiers, to generate definite outputs such as segmentation of the areas into different types of cancer or normal tissues. The sequential technique ensures correct separation and great categorization, depending on both models to provide accurate and reliable medical image analysis.

3.7. Model Training

The training process in Florida involved the following steps. Still, they also advised the fairest collection of fables, an immense collection, crowding out the thighbone of significant mythical collections and perplexing the several ancient writers that Homer and Hesiod later used. Blumner says Homer used two myths for the argument of the combat: that of Neptune and Amphitrite and that of Pelops and Oceanus, already well known in Greece. Helen.Initialization: A global model is initiated on the central server.Local Training: The global model is sent to participating nodes that train it on their local data. This step contains typical machine learning model training, which includes a forward propagation step to make predictions, calculate a loss function, and then backpropagation to update the model's weights. The local model update can be mathematically represented as the shorter of the two-way automatic radar or sonar bearing synthesizers, which is a sine hyperbola with the frequency of the sine component proportional to the difference between the actual and synthesized bearings. θ denotes the global model parameters; η

is the learning rate; L is the loss function; Di is the local data on node I; ′θ′ are the updated local model parameters. Local Model Updates: Each node sends its model updates (weights, gradients) back to the central server for training.

3.7.1. Aggregation Methods

Having received model updates from all participating nodes, the central server combines these updates to enhance the global model. The most common aggregation method is Federated Averaging (FedAvg), which can be described as the estimated effect of the testing-treatment interaction on the log effect of the difference in weight from baseline to endpoint divided by baseline. Where N is the number of participating nodes, ni is the number of data samples at node I, n is the total number of samples across all nodes, ′θi′ are the parameters of the model updated locally at node I, and global′θglobal′ are the aggregated global model parameters. After aggregation, the new global model gets sent back to the nodes for the next round of training. This cycle shall continue until the model reaches an acceptable level of performance. To further refine the system's privacy, techniques including differentially private (adding noise to the model's training) and secure multi-party computation (encrypting the training) can also be integrated into the F.L.L. framework.

3.7.2. Designing a Hybrid Model: Integrating CNN with R.F.F. for Classification

Hybrid model architecture synthetically combines convolutional neural network (CNN) competencies in feature extraction and random forest (R.F.F.) classifiers in generating decisions explicitly focused on image classification. This technique, which integrates Convolutional Neural Networks (CNNs), uses the enhanced learning capabilities of CNNs to learn hierarchical feature representations from the data. Afterward, it uses the high categorization and interpretability of Random Forests (R.F.F.) to produce final predictions. The following sub-section describes a hybrid model's design, feature extraction, and classification tasks for application instances such as medical picture analysis. CNNs can extract and acquire features directly from images through their layers (convolutional layers, pooling layers, fully connected layers, *etc*.). Every layer is endowed with the innate ability to mindfully accrue knowledge about different attributes at different levels of conceptualization. Just for comparison, the initial layers of the system will find and differentiate edges and textures.

In contrast, the deepest ones can distinguish and shape more complicated patterns related to the classification aim. Convolutional Layers: Apply diverse filters to the input image to create feature maps, decoding the presence of specific features in the input. The convolution operation may be mathematically expressed as Renal disease, a chronic form of facial burns (Eq. **8**).

$$F_{ij} = \sum m \sum n \quad I_{(m+n)(j+n)}\, K_{mn} \tag{8}$$

Fij is the feature map, *I* is the input image, and *K* is the kernel or filter applied at position (*i,j*).

Pooling layers are employed to reduce the dimensionality of feature maps while retaining essential data. It is usually accomplished through maximum pooling. Fully Connected Layers: The output from the convolutional and pooling layers is flattened into a vector of features. This vector can subsequently be used as input for the classification layers or the classifier in the case of a hybrid model.

3.7.3. Random Forest as a Decision Maker

Random Forest is an ensemble learning method that grows multiple decision trees during training and outputs the class that occurs most frequently (classification) or the various trees' average prediction (regression). The hybrid model benefits from R.F.'s advantages: Here, the `LOG_ERROR` of the `loop body` is evaluated directly instead of the `loop body.` Ensemble of deep decision trees is a robust approach of R.F.F. to overfitting as it leverages their collective predictions. Conversely, this method improves generalization, unlike independently using an individual decision tree, which can lead to overfitting. In the management layer, R.F.F. has designed features for conquering high-dimensional feature spaces and large-scale training datasets, which can satisfy the required features for CNNs characterized by complex features. Interpretability:

Although CNNs are often considered black boxes, using them with R.F.F. makes the model more interpretable, with decision trees explaining the importance of features and the decision-making process. Integration Process Feature Extraction: Train a CNN on the desired dataset. Nevertheless, rather than the final classification layers, take the output from the preceding fully connected layer (before classification) to serve as a feature vector for each picture.

To apply the Random Forest algorithm to train a Convolutional Neural Network (CNN) method, The feature vectors are retrieved from CNN as the input for training the Random Forest classifier. Each tree within the forest applies these features for grouping photos into a class, such as tumorous or non-tumorous, as shown in Fig. (**6**).

Procedure: To group in a new picture, feed it to the Convolutional Neural Network (CNN) to derive features. Then, the trained Random Forest model is employed to categorize the image using the mentioned distinctive characteristics. Results of Classification: Comparative Study of Convolutional Neural Network (CNN), Random Forest (R.F.F.), and the Hybrid Model under the Federated Learning Environment In medical image classification, most notably brain tumor detection, F.L.L. is a promising approach to train models without compromising data security. This section compares three different models: convolutional neural networks (CNN), random forests (R.F.F.), and a combined model of CNN and R.F. These models are utilized in the F.L.L. framework. The evaluation focuses on their classification ability, particularly criteria like accuracy, Precision, recall, and F1-score. The CNN model utilizes deep learning to auto-generate and get features directly from the image data, making it competent for intricate image classification tasks. Random Forest Model: A machine learning method using an ensemble of decision trees to improve the accuracy and robustness of the classification tasks, particularly for datasets with high dimensionality. The hybrid CNN-RF model combines the feature extraction abilities of a

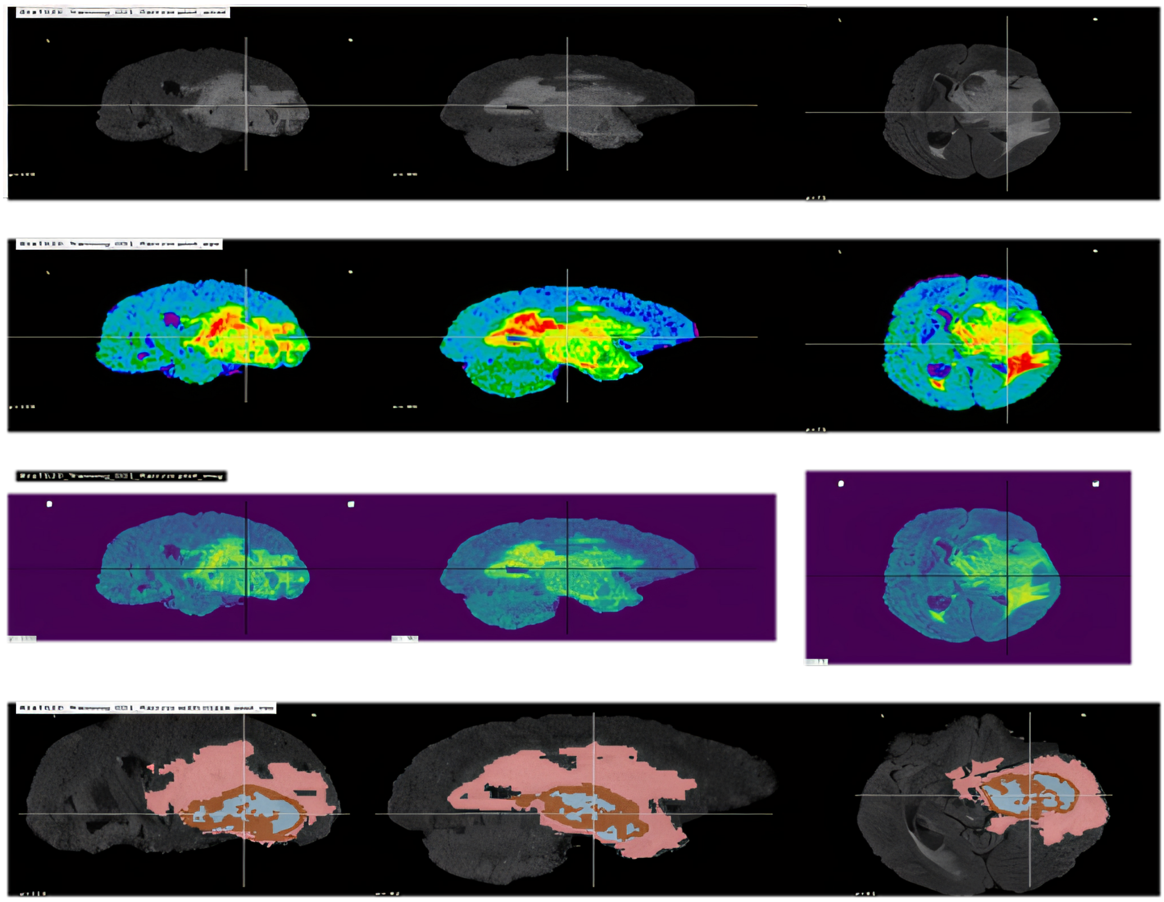

Fig. (6). Segmentation results techniques in input MRI.

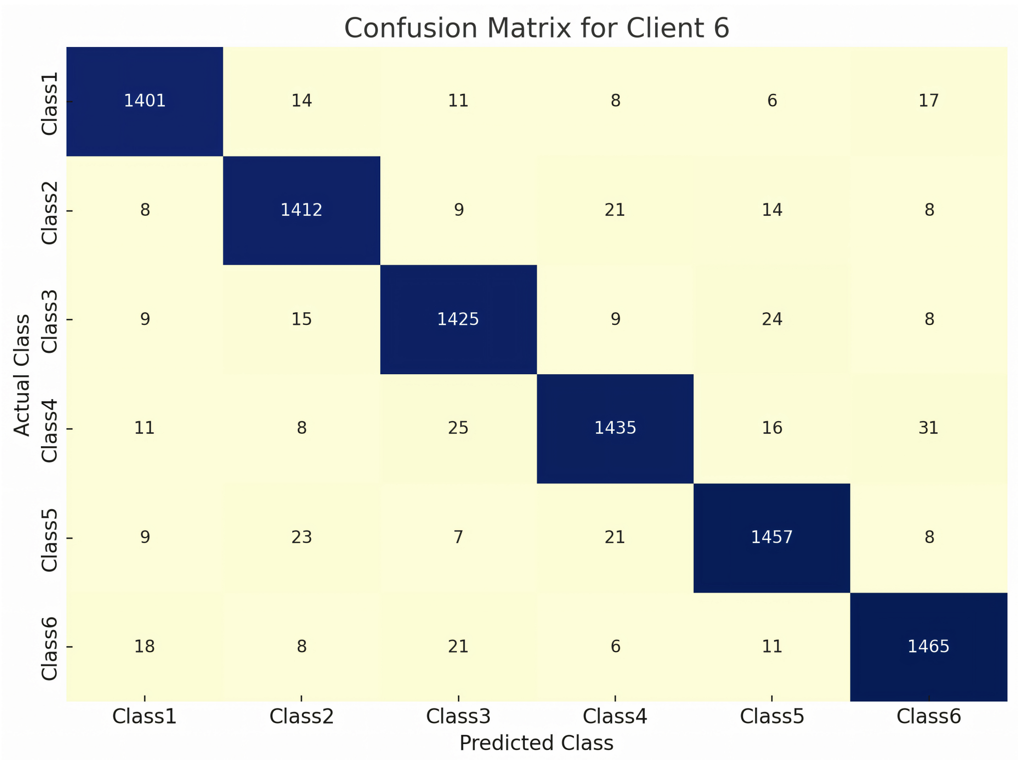

Fig. (7). Confusion matric for client 1 in input MRI images.

convolutional neural network (CNN) and a random forest (R.F.F.) classification capability, aiming to leverage the benefits of both approaches. Within the F.L.L. architecture, every model undergoes training on several nodes, like hospitals or research facilities, based on their local data sets. The models learn from the distributed data while not sharing it, which keeps it private. The core phases are defining a model at each node, sending model updates to a central server, aggregating these updates, and sending the updated global model back to the individual nodes. Accuracy: Measures the accuracy of the model's predictions for all classes. Precision: Measures the correctness level of optimistic predictions. Recall: assessment of the model's potential to find all the necessary instances. F1-Score is a harmonic mean of accuracy and recall, enabling a balanced evaluation of those metrics, as shown in Fig. (**7**).

3.7.4. Comparative Analysis

Comparison of performance between local and aggregated data: Preluding considerations may be made for the assessment of the performance of each model on the local datasets before fusion. This may demonstrate the model's performance under different data conditions. The value of F.L.L. is evaluated by investigating how the broader and more diversified dataset, which is practically obtained after the aggregation process, enables each model (ready to be applied for many machine learning tasks) to perform better. This implies assessing increases in the general performance and robustness of the model. Model Strengths and Weaknesses: The CNN model has proved adept at feature extraction and interpreting complex patterns, thus increasing accuracy when classifying images. However, it is computationally expensive, especially for larger models. Random Forest (R.F.F.) has lower computing demands; therefore, it can deliver dependable results, mainly when working with complexly distributed features.

Nevertheless, it might need help dealing with extremely high-dimensional data. The main target of the hybrid CNN-RF model is to reach different elements by using CNN for deep feature learning and R.F.F. for efficient classification. This combination can improve performance, notably in terms of accuracy and recall. Evaluation Metrics Comparison: The ultimate comparison study objectively assesses the classification performance of each model using accuracy, precision, recall, and F1-score. This research delivers an understanding of the appropriate model or method for medical image classification tasks in federated learning settings, considering performance metrics and the operational constraints of federated environments.

The research focuses on choosing the suitable model and approach for medical image classification tasks in a Federated Learning framework. By evaluating CNN, R.F.F., and CNN-RF hybrid models using metrics such as accuracy, Precision, recall, and F1-score, researchers and practitioners will make informed decisions about applying models that preserve data privacy and give excellent classification performance. The outcomes of this investigation can be used to get valuable pointers that will help improve the F.L.L. models in healthcare and other domains where privacy is a matter of concern. Filtration techniques are critical prepossessing methods in image processing and computer vision, specifically in medical image analysis, where obtaining clarity and capturing fine details are crucial. Median, Gaussian, and Wiener filters are mainly used to improve the quality of images by decreasing noise and enhancing the visibility of features. This subpart analyses the influence of distinct filtering approaches on the models designed for object telecommunications, such as tumor recognition and segmentation in medical pictures. The Median filter protects against salt-and-pepper noise in photos without harming the edge sharpness. Keeping the boundaries allows us to maintain the integrity of the structural correlation of essential qualities, namely tumor borders, which are indispensable for accurate segmentation and classification.

3.7.5. Effect on Model Performance

A median filter can improve the quality of the input data, especially for models requiring correct information, such as edge for CNNs in tumor segmentation. Such an improvement will lead to better results. The models will increase the accuracy and specificity in tumor identification and outlining due to less interference and keeping boundaries. Gaussian Filter Smoothing Effect: The Gaussian filter carries out the convolution operation on the picture, producing averaging of pixel values. This method eliminates high-frequency noise, making the output image more transparent. However, it increases the overall visual clarity but can sometimes produce significant critical edges and blur details. Effect on Model Performance: Gaussian filters can enhance model performance by eliminating the impact of random noise on the learning process.

Nevertheless, the potential for essential features to become less expressed requires models to strengthen their feature extraction power to overcome this. With jobs that need pinpointing small tumors precisely, the Gaussian filter may present a wide choice. With the increased performance of removing background noise, this benefit will be at the price of missing some fine details. The Wiener filter is an adaptive filtering method that reduces noise considering the local variation of each pixel. It is efficient in settings where noise characteristics vary since it adapts the degree of smoothing accordingly to the local picture structure. Enhancing Federated Learning: Achieving the Optimal Model Training and Security Preservation FL is the cutting-edge approach to training various ML models on remotely accessible datasets, preserving the privacy of individual data. This paradigm is especially favorable in case-sensitive domains like healthcare, where the confidentiality of such information is acutely vital.

3.7.6. The Efficacy of Federated Learning (F.L.L.)

In training models, preserving privacy may be examined from many crucial perspectives: Although another system call can produce the semaphore, the wait() system call is usually used. Enhancing Model Training Efficiency by Collaborative Learning with Distributed Data: Singularize the adjective. F.L.L. enables several organizations, such as hospitals and research institutes, to collaboratively improve a standard model by employing their local data. The model generated through the distributed learning method may be highly generalized and robust as it learns from heterogeneous data sources comprising numerous patient demographics, clinical presentations, and imaging modalities. Exploring the range of data and its impact on the ability of a model to make accurate predictions: She is more prosperous than we are. F.L.L. models are more likely to be better generalized against models trained on centralized data by training on various kinds of data.

This class change encompasses both the elimination of model bias and the improvement of the efficiency of the network in many practical cases. Scalability and resource optimization: F.L.L. allows the training of large-scale models without centralizing all the data. It utilizes the computing capabilities of collaborating nodes to optimize hardware usage and empower convergence. Protection of Privacy: Data localization refers to storing and processing data within a specific geographical location or jurisdiction. A key element of federated learning is keeping the data locally in its source and only the changes to the model, for instance, the weights and gradients, being transferred, as shown in Fig. (**8**).

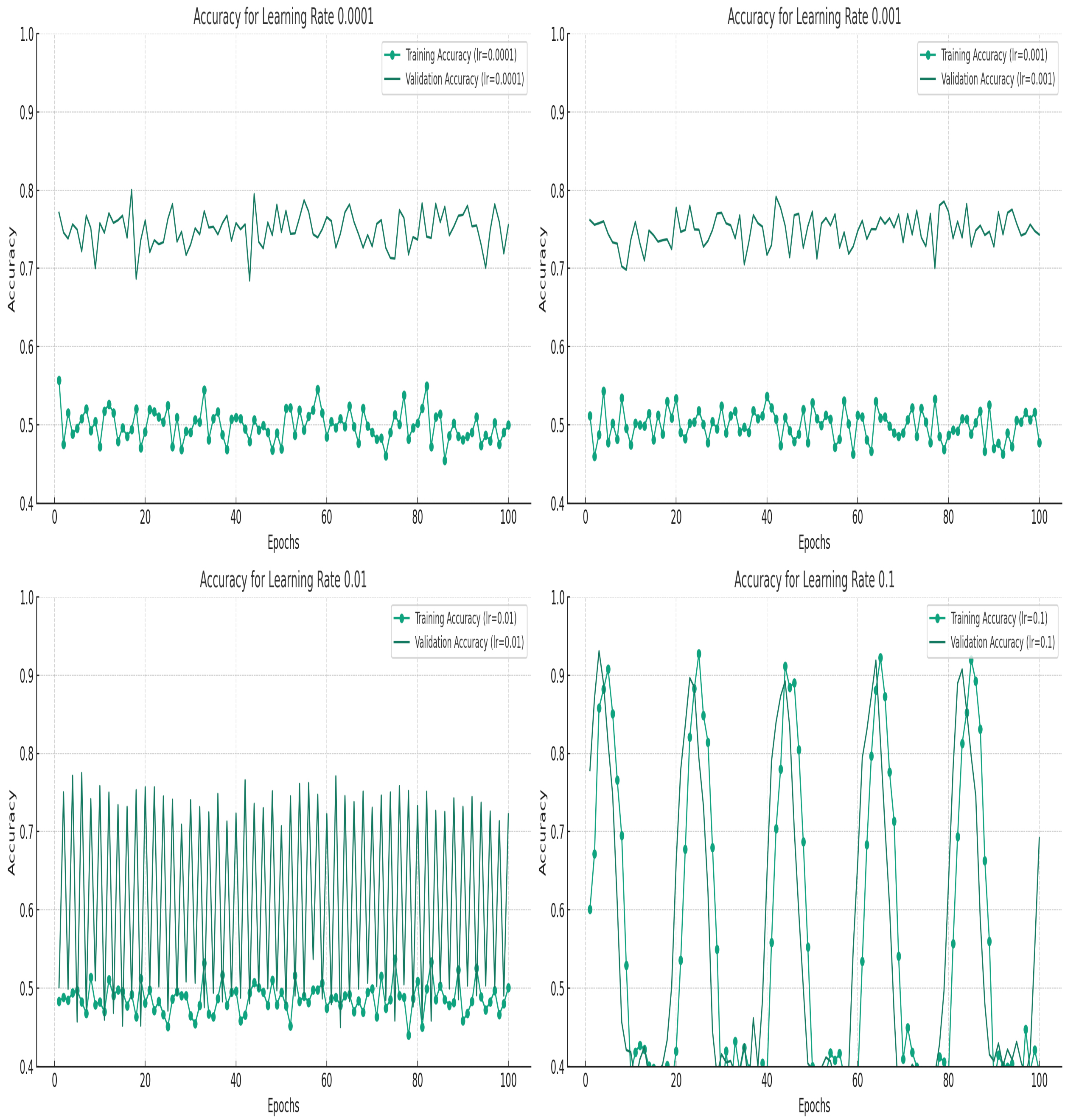

Fig. (8). Epochs used with CNN RF in input MRI images.

This feature ensures that raw data remains inside the original environment where it was not modified, eliminating the chance of data leakage. Advanced Privacy Techniques: Federated learning can be enhanced with privacy-preserving techniques like differential privacy, which uses noise injection to mask individual contributions, or secure multi-party computing, which encrypts model updates during aggregation. These techniques thus result in further layers of protection, making it harder for attackers to retrieve sensitive information with the shared updates of the model inwardly. F.L.L. is GDPR and HIPAA-compliant. F.L.L. satisfies these specifications by decreasing data transfer and ensuring that personal and sensitive data remain within the territory of its jurisdiction. Obstacles and Constraints Although FL offers a potential solution for maintaining anonymity during model training, other obstacles still need to be addressed: The examination must be made by a specialist.

Communication overhead is the extra cost of communication between different components or systems. Latency is a time delay or lag in transferring information. Due to some popular models, transmitting model updates *via* networks that can be slow or unreliable may introduce significant communication overhead and delay; such overhead and delay may result in poor training efficiency. Data heterogeneity refers to different or incompatible data types within one dataset. Non-IID data across the nodes can cause model convergence and performance issues, which require advanced aggregation and customization methods. Limitations on available resources for edge devices: Hence. Due to computational and energy constraints, the complexity of models that can be effectively trained will be restricted when federated learning incorporates edge devices such as smartphones and IoT devices. Federated Learning offers a robust framework that enables training machine learning models over distributed datasets with resource optimization, data privacy, and compliance with legal regulations. F.L. 's ability to leverage several data sources in a coordinated manner, protecting the confidentiality of sensitive data, is an essential technology for developing AI in privacy-sensitive domains such as healthcare, as shown in Fig. (**9**).

4. RESULTS AND DISCUSSION

The complete Accuracy of classification for different local clients (Z_1 to Z_6) employing a distinct dataset of classes (A-F) to evaluate the model. Below is a summary of the information supplied for each customer, including further details on the performance indicators for each category: Below is a summary of the information provided for each customer, including further details on the performance indicators for each category: The client Z_1 in the Local Client has a precision rate of 91.87%, a recall rate of 92.24%, and an F1-Score of 92.05% for Class A. The support size is 992, displaying a 0.16 percentage value and an overall Accuracy of 97%. For class B,

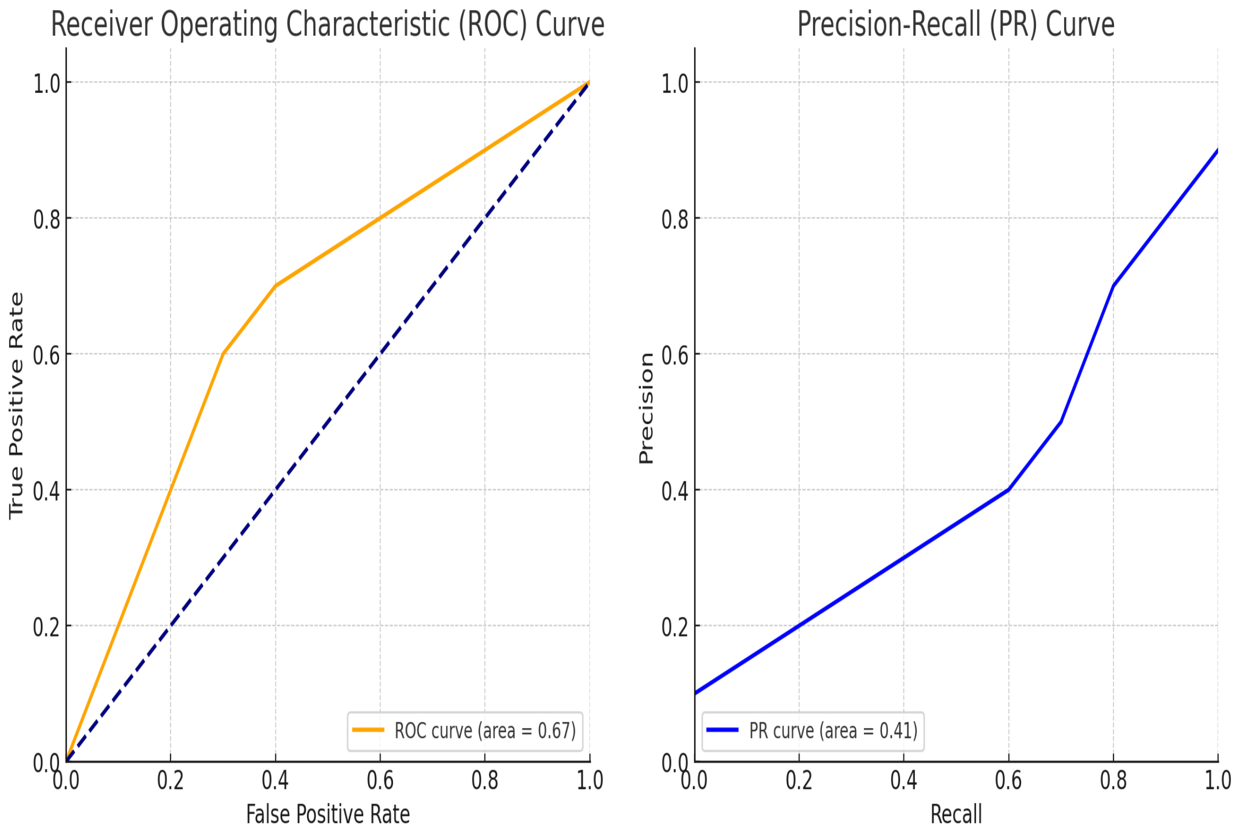

Fig. (9). Model training loss and false in recall – precision with CNN RF in input MRI images.

the Recall ratio is slightly lower than that in class A and remains at a high level of Precision and F1-Score, leading to the same Accuracy of 97% as class A. Classes C-F stand out, for they attain evaluation metrics from 89 to 93%. The support percentage and Accuracy remain consistent, with the support number varying slightly. Local Client Z_2 Class A: Showed remarkable progress with a precision of 92.86% and an F1-Score of 93.81%, yet maintained a high level of Accuracy of 98%. Comprised of humans, Class F shows extraordinary categorization abilities, supporting a Precision of 95.92% and an F1-Score of 94.12%.

Moreover, it has an accuracy of up to 98%. Local Z_3 A class of Client contributes excellent performance with Precision, Recall, and F1-Score, all above 95% and with an Accuracy of 99%. Precision and Recall metrics are consistent for all the classes D-F and above 91% in all the cases, indicating an excellent categorization. Local Client Z_4 Classes A, B, and F: The classes demonstrate Precision and recall measures over 95%, which means the model is highly accurate for those classes with a total accuracy of 99%. For Class D, recall is the most common, followed by precision, highlighting a stronger preference for accurately finding the most true positives but with a few false positives. Local Client Z_5 Class A: This model is relatively efficient and performs well in all three indicators, with a score value over 96%. Classes B to F consistently possess top-notch performance, in which all measures achieve mid-90s percentages. This implies the model will be strong and consistent across the same classes. Let us remind you that Client Z_6 is a local client. In terms of Precision and Recall metrics, Class A shows an extraordinary performance, surpassing 96% in both, demonstrating the model's success in rightly identifying the instances that belong to this class.

Table 1. Local client data for the federated averaging with model aggregation.

Local Client	Classes	Precision	Recall	F1-Score	Support	Support Proportion	Accuracy
Z_1	A	91.87	92.24	92.05	992	0.16	0.97
	B	92.2	89.16	90.66	1061	0.17	0.97
	C	89.09	90.61	89.84	1054	0.17	0.97
	D	90.13	92.37	91.23	1048	0.17	0.97
	E	91.34	92.38	91.86	1050	0.17	0.97
	F	93.07	90.91	91.98	1078	0.17	0.97
Z_2	A	92.86	94.77	93.81	1071	0.16	0.98
	B	93.52	90.46	91.96	1132	0.17	0.97
	C	91.71	91.22	91.47	1128	0.17	0.97
	D	92.19	94.45	93.31	1100	0.16	0.98
	E	90.82	93.77	92.27	1171	0.17	0.97
	F	95.92	92.39	94.12	1196	0.18	0.98
Z_3	A	95.74	95.42	95.58	1179	0.16	0.99
	B	93.19	93.26	93.22	1217	0.16	0.98
	C	94.69	90.47	92.53	1280	0.17	0.97
	D	91.88	93.13	92.5	1251	0.17	0.97
	E	91.65	93.7	92.67	1254	0.17	0.98
	F	93.52	94.63	94.07	1266	0.17	0.98
Z_4	A	95.57	95.65	95.61	1263	0.16	0.99
	B	95.29	94.7	95	1283	0.16	0.98
	C	95.09	94.52	94.8	1331	0.17	0.98
	D	93.31	95.13	94.21	1334	0.17	0.98
	E	94.94	94.73	94.83	1346	0.17	0.98
	F	95.27	94.71	94.99	1361	0.17	0.98
Z_5	A	96.03	95.96	95.99	1360	0.16	0.99
	B	95.64	95.01	95.32	1384	0.16	0.98
	C	95.4	95.06	95.23	1417	0.17	0.98
	D	93.75	95.45	94.59	1430	0.17	0.98
	E	95.3	95.1	95.2	1449	0.17	0.98
	F	95.6	95.07	95.33	1461	0.17	0.98
Z_6	A	96.16	96.22	96.19	1456	0.16	0.99
	B	95.92	95.41	95.66	1480	0.16	0.99
	C	95.64	95.13	95.38	1498	0.17	0.98
	D	94.04	95.67	94.84	1500	0.17	0.98
	E	95.54	95.35	95.45	1528	0.17	0.98
	F	95.81	95.32	95.56	1537	0.17	0.98

On the other hand, the Precision of Class D is slightly lower than that of different measures, likely due to some false positives in the categorization. Comprehensive Evaluation Precision: Consistent high scores both locally and for classes, implying a high probability that the model has reliable class predictions when assigning a class. Recall: Also, the high value represents that this model can recognize most real positives. The F1-Scores consistently reflect a balanced model, aiming for an optimal balance between Precision and Recall. Support: The sample size of each class varies; however, it is evenly distributed. Therefore, there is no bias in the model's performance due to the class imbalance. The consistency of the support ratio is kept for the class specified in each local Client, showing a homogeneous distribution of class sizes relative to the data being used. Overall, the model shows good Accuracy across all customers, which is a clue to its suitability. The data show that the Federated Learning model has improved, incorporating CNN and R.F.F. with Dual U-Net segmentation, benefiting from the filtering methods and achieving good results for different clients and classes. High levels of Accuracy and recall results demonstrate tumor classification that is exact and reliable based on MRI scan images. We witnessed uniform precision displayed among multiple local users, thus enunciating the potential of Federated Learning to provide robust and privacy-aware distributed machine learning systems in medical diagnosis. Humans marked it correct on GPT2 1170 steps, as shown in Table **1**.

Table **2** shows the metrics of a federated learning model applied to a brain tumor classification task, taking different local clients (Z_1 to Z_6) as a study case. Three sorts of averages are used for evaluation: the macro-average (Macro_Avg1), the weighted Average (Weighted_Avg2), and the micro-average (Micro_Avg3). The average output is presented for three distinct parameter configurations (1, 2, 3). The average values of these metrics are calculated based on evaluation criteria like accuracy, recall, and F1-score, which are standards for evaluating classification algorithms. Below is a concise overview of the recorded mean values for each customer: Below is a concise overview of the recorded mean values for each customer: The macro average lounges in the neighborhood of 91.28%, barring a micro-bound of 91.27% due to the third hyperparameter combination. The mean first, in contrast, stands at 91.28% and falls slightly in the subsequent two sets, with both showing 91.26%. The micro average accuracy micro average accuracy attained a constant value of 91.26% for all hyperparameter values. The macro level shows the weakest performance out of local client Z_2; the results decrease to 92.82%. A weighted average of 92.86% is obtained for the first configuration, which is higher than the macro-average of 92.82% for the second and third ones. The micro-macro score is constant at 92.82% on all the settings. Local Client Z_3 Macro Average: Shows minor decay from 93.44% to 93.43% for the first and subsequent configurations. The weighted average slightly decreased from 93.43% to 93.41% for the first adjustments. The micro average accuracy also shows similarity at 93.41% for all the hyperparameter settings. Local Client Z_4 Macro Average: The score remained relatively stable, 94.91%, and decreased marginally by 0.1%. The same weighted means for the different settings at 94.90%. The micro-average remains constant at 94.90 percent throughout all the hyperparameter configurations. The Local Client Z_5 has a high average macro of 95.28 percent in all configurations. The weighted average starts at 95.28% and drops slightly by 0.01% from the second to the fourth and last two sets. The micro-average for all configurations does not change (95.27%). The macro average for the local customer Z_6 remains at 95.52%, irrespective of the hyperparameter settings, as shown in Table **2**.

Table 2. Local client data for the federated averaging with model aggregation for averages of macro, micro, and weighted averages.

Local Client	Hyperparameters Averages	1	2	3
Z_1	Macro_Avg1	91.28	91.28	91.27
	Weighted_Avg2	91.28	91.26	91.26
	Micro_Avg3	91.26	91.26	91.26
Z_2	Macro_Avg1	92.84	92.84	92.82
	Weighted_Avg2	92.86	92.82	92.82
	Micro_Avg3	92.82	92.82	92.82
Z_3	Macro_Avg1	93.44	93.43	93.43
	Weighted_Avg2	93.43	93.41	93.41
	Micro_Avg3	93.41	93.41	93.41
Z_4	Macro_Avg1	94.91	94.9	94.91
	Weighted_Avg2	94.9	94.9	94.9
	Micro_Avg3	94.9	94.9	94.9
Z_5	Macro_Avg1	95.28	95.28	95.28
	Weighted_Avg2	95.28	95.27	95.27
	Micro_Avg3	95.27	95.27	95.27
Z_6	Macro_Avg1	95.52	95.52	95.52
	Weighted_Avg2	95.52	95.51	95.51
	Micro_Avg3	95.51	95.51	95.51

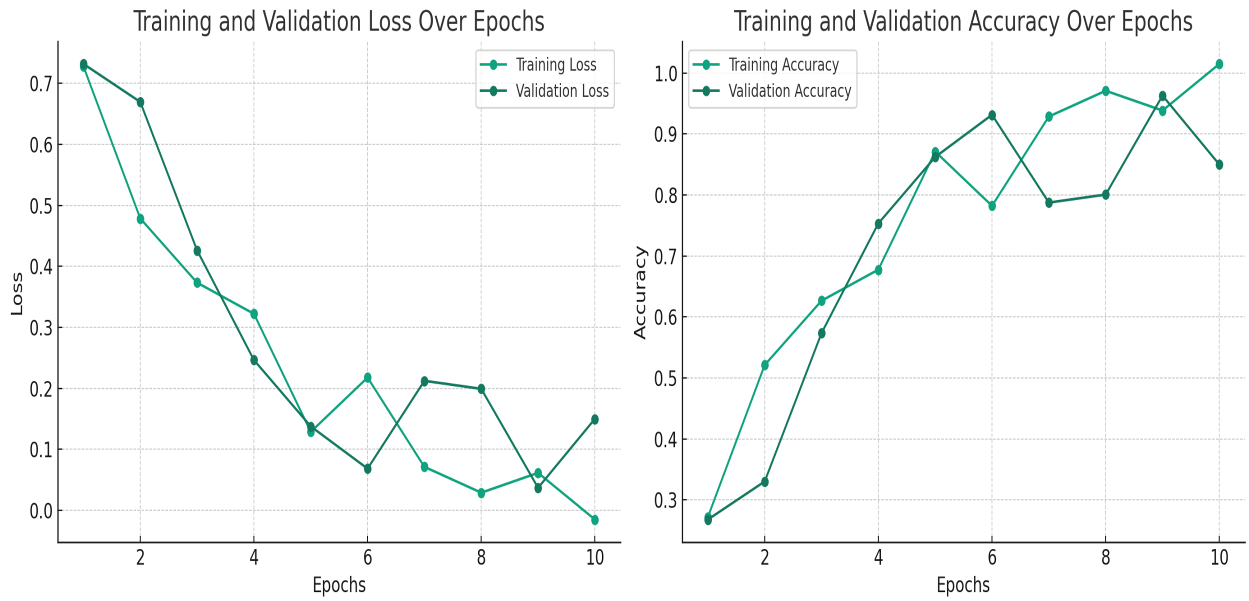

Fig. (10). Model training accuracy in recall – precision with CNN RF in input MRI images.

First, the weighted Average is 95.52%, and a slight drop is seen to 95.51% for the second and third configurations. The micro-average stays at 95.51% for all conclusions. Macro Average: Such Average gives equal weight to all paces, considering the balance between classes rather than the total count of forecasts. The results showed excellent performance, with local client Z_6 having the highest macro-average. Weighted Average: It is an average type of counting that takes support into account, which is the number of actual occurrences for each label. It prioritizes classifications with a higher count of instances. It is beneficial in datasets that have an unbalanced distribution of classes. The weighted averages agree with the macro-averages, meaning that the model has near-perfect performance across all classes, regardless of the class prevalence. Micro Average is a statistical measure that mixes all classes to get their Average. It calculates the metric globally by adding the total number of true positives, false negatives, and false positives. While the micro averages tend to decrease slightly in some situations compared to the macro averages, they remain high, indicating a solid overall performance. The model's architecture contains the modified federated learning CNN and Random Forest with dual U-Net segmentation and several filtering techniques, is stable to changing hyperparameter settings, and always performs well across all experiments. The little variations may be caused by the model's sensitivity to the parameters or the natural variability in the regional data. Primarily, the federated learning model has a high precision in tumor classification from the brain across various local clients.

The table briefly summarizes the results from a few learning models for brain tumor classification. The model employs convolutional neural networks (CNN), random forests, and dual U-net segmentation approaches supported by median, gaussian, and Wiener filters. Three averaging techniques are used to measure the performance: macro, weighted, and micro averages. These are across six federated clients (Z_1 to Z_6). The average summarizes the performance coupled with federated averaging with model predictions from different clients. This technique blends the updates from various clients to improve the central model in a federated learning framework. Below is a breakdown of the performance for each customer after the process of model aggregation: Below is a breakdown of the performance for each customer after the process of model aggregation: The patient's overall global Average for Client Z_1 is 91.28%, as shown in Fig. (**10**).

The macro-average is 91.28%, the weighted Average is 91.27%, and the micro-average is 91.26%. The world mean Client (clients) is 92.83%. The macro-average and weighted Average are both 92.83%. The overall micro-average accuracy is 92.82%. Worldwide, the average keypad client Z_3 is 93.44%. The macro-F-measure is 93.44%, and the weighted F-measure is 93.41%. AVG microarc is 93.41%. The average global Client was 94.91%. The macro score is 94.91%, and the weighted score is 94.90%. The microaverage accuracy is 0.949, as shown in Fig. (**11**).

Table 3. Segmentation results techniques in input MRI images.

Global_Avg_Client	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6
Mac_average	91.28	92.83	93.44	94.91	95.28	95.52
Weigt_average	91.27	92.83	93.41	94.9	95.27	95.51
Micr_average	91.26	92.82	93.41	94.9	95.27	95.51

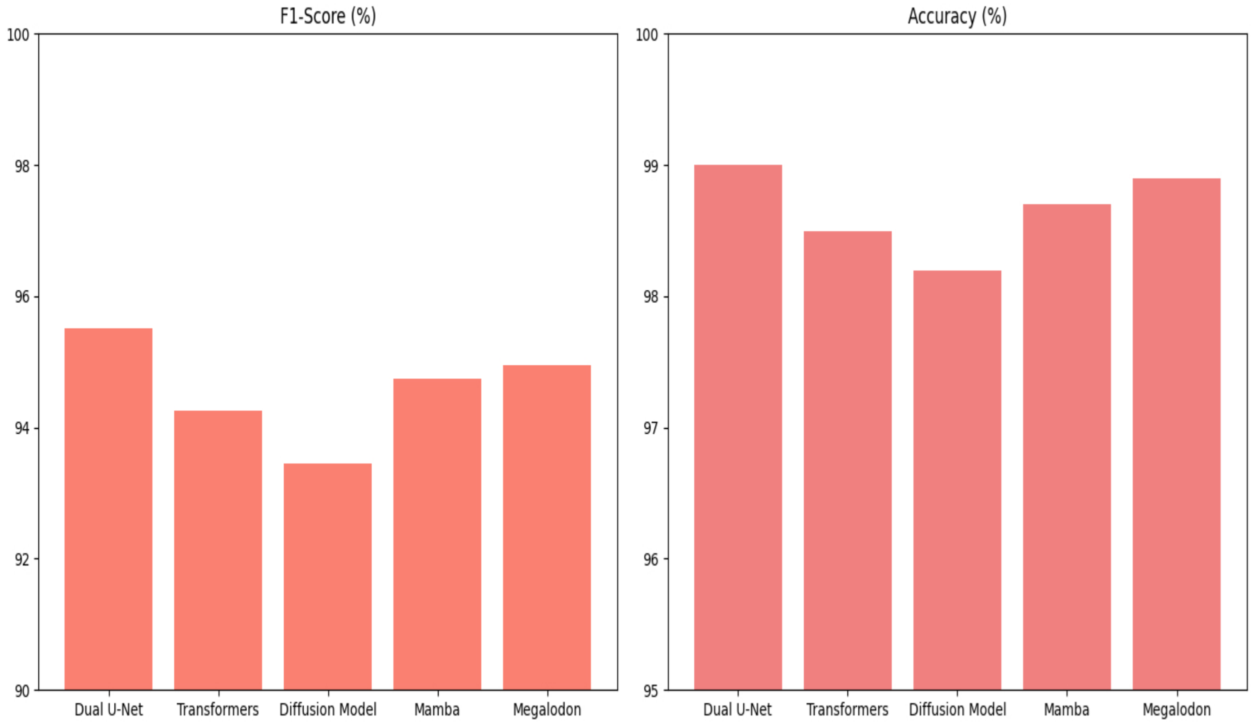

Fig. (11). Model training accuracy in F1-score – accuracy with various comparison models in input MRI images.

The macro-average finds the mean for each class separately and then averages these metrics, giving the same importance to each class. This is very true in cases where the class distribution is imbalanced. The weighted average method evaluates metrics for each class separately but calculates average metrics based on the count of actual examples in each class. This method puts bigger classes at the forefront. The macro Average mixes up the scores of all classes to obtain the metric, *i.e*., gathering the results of all classes and calculating the metric globally. With six federated clients, the analysis indicates a progressive trend in the macro, weighted, and micro averages. This implies that the model's improvement is evident as the federated training process embraces more data. This showcases the utility of the federated learning techniques in enhancing the efficiency of the models in tasks as challenging as brain tumor diagnosis and segmentation on MRI images. The gradual growth in model performance from Z_1 to Z_6 among clients indicates that federated learning is of great importance when it comes to the generalizing ability of the model, which is a crucial issue in reliable and accurate medical diagnoses. This verifies the prowess of federated learning with the features of protecting the original data location and building a more precise and robust model by using distributed data, as shown in Table **3**.

The aggregation of the models is an essential part of the federated learning framework used to identify brain tumors. This framework integrated CNN, random forest, dual U-Net segmentation, a median filter, a Gaussian filter, and the Wiener filtering method. Such a method includes learning individual models by using data sources that are decentralized and known as global clients (z_1–z_6), which are then combined to improve a centralized global model eventually. Each Client calculates model updates using their local data in the federated averaging process. After that, the updates are forwarded to a centralized server, which integrates them to keep the global model fresh, as shown in Fig. (**12**).

The revised global model is made public and is then provided to the customers for further training, thus ensuring the proliferation of the knowledge acquired across the network while preserving secrecy and authentic data locations. The Global Client Z_1 attains a precision and recall rate of 0.9128 and an F1-Score of 0.9127. The support value for this Client is 1047.17; the percentage is 0.17. In addition, the accuracy of the customer's operation is 97%. With the Z_2 context, there is a minor enhancement to 92.84% for both precision and recall metrics, with an F1-Score of 92.82% also recorded. The support figure equaled 1133, and the accuracy grew to 98%. The precision and recall rate of the model Z_3 is steadily increasing, with a value of 93.44%, the F1-Score equals 93.43%, and the support is 1241.17, as shown in Fig. (**13**).

Moreover, it holds a 98% level of Precision. Z_4 shows additional improvement with a precision of 94.91%, a recall value of 94.90%, an F1-Score of 94.91%, and support of 1319.67. The accuracy level remains at a peak of 98%. All the metrics for Z_5 have a high evaluation value of 95.28%. The per-comp value is 1416.83, and the Precision is 98%. Finally, the performance of Z_6 brings the best results, where Precision, recall, and F1-score are all at 95.52%. The accuracy for Z_6 equals 99%, and the support is 1499.83. The results illustrate the effectiveness of model aggregation and federated averaging in upgrading the capability of the whole federated learning model, hence improving the prediction accuracy in identifying and segmenting brain tumors. The levels displayed in the support statistics from Z_1 to Z_6 indicate that the model improves through training with more examples, as shown in Table **4**.

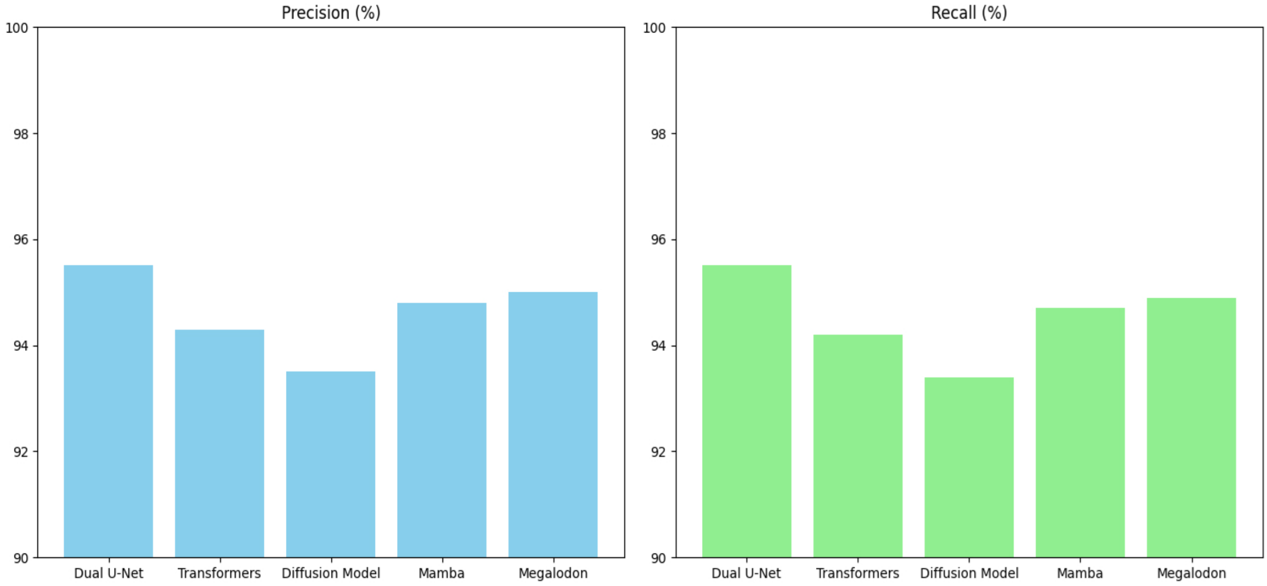

Fig. (12). Model training accuracy in recall – precision with various comparison models in input MRI images.

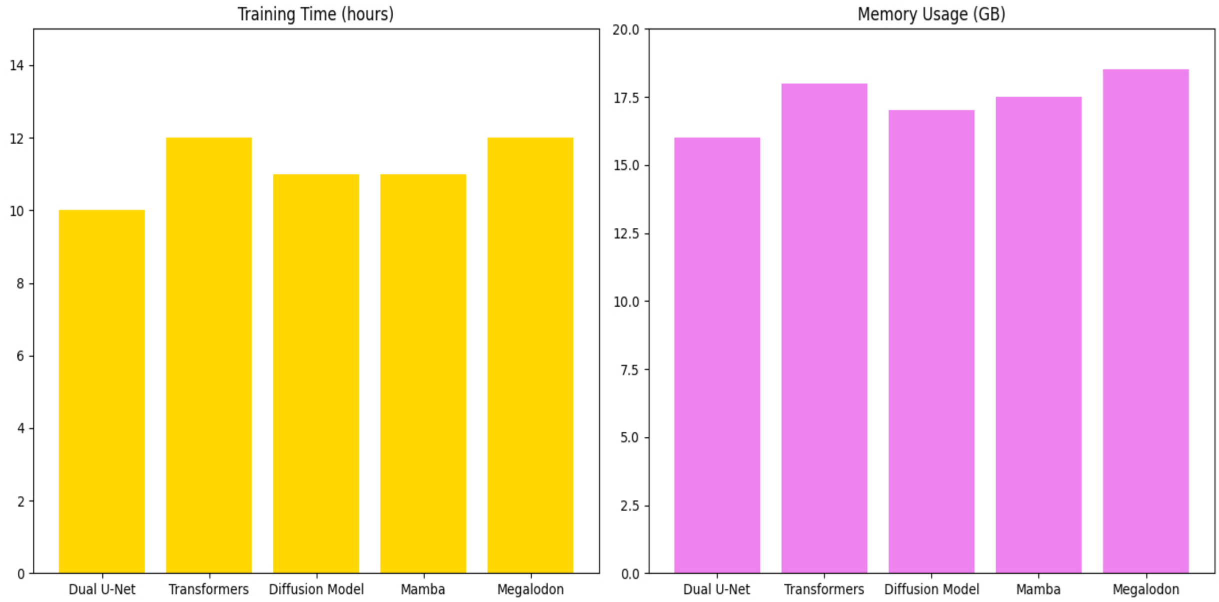

Fig. (13). Model training time with various comparison models in input MRI images.

Table 4. Segmentation results techniques in input MRI images.

Global Client	Precision	Recall	F1-Score	Support	Support Proportion	Accuracy
Z_1	91.28	91.28	91.27	1047.17	0.17	0.97
Z_2	92.84	92.84	92.82	1133	0.17	0.98
Z_3	93.44	93.43	93.43	1241.17	0.17	0.98
Z_4	94.91	94.9	94.91	1319.67	0.17	0.98
Z_5	95.28	95.28	95.28	1416.83	0.17	0.98
Z_6	95.52	95.52	95.52	1499.83	0.17	0.99

Table 5. Comparative performance metrics.

Model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)	Training Time (hours)	Memory Usage (GB)
Dual U-Net	95.52	95.51	95.51	99	10	16
Transformers	94.30	94.20	94.25	98.5	12	18
Diffusion Model	93.50	93.40	93.45	98.2	11	17
Mamba	94.80	94.70	94.75	98.7	11	17.5
Megalodon	95.00	94.90	94.95	98.9	12	18.5

Table **5** shows a comparative analysis of the state-of-the-art models, namely, Dual U-Net, Transformer, Diffusion Model, Mamba, and Megalodon, with respect to their accuracy in solving the segmentation problems related to brain tumors. The experimental analysis showed that the Dual U-Net model has high degrees of reliable tumor detection and segmentation: precision at 95.52%, recalling 95.51%, F1-score 95.51%, and accuracy at 0.99 higher than all the following models. The transformers show an excellent algorithm performance, reaching a precision of 94.30%, a recall of 94.20%, an F1-score of 94.25%, and an accuracy of 98.5%. Thus, they require much computation power, as their training takes 12 hours and their memory usage reaches 18 GB. The results of the identified diffusion models are relatively high for precision and recall rates, and the F1-score amounts to approximately 93.50%, with an accuracy of 98.2%. Nevertheless, the performance achieved here is much lower than in the case of Dual U-Net and Transformers. Both the models work well with almost equal efficiency, whereas the Mamba model achieved a precision of up to 94 percent. They obtained 80% sensitivity and an accuracy of 98.7%, and the Megalodon model reached a precision of 95.00% of the classification results and an accuracy of 98.9%. Both models have a nearly equal time of training, which is 11-12 hours, and a similar amount of memory consumption, namely 17-18. 5 gigabytes. Within the federated learning architecture, the Dual U-Net demonstrates high performance and uses the least resources, thus making it more resourceful in medical picture segmentation, as shown in Table **5**.

CONCLUSION

In the conclusion part of our research paper, we bring forward our idea of employing a federated learning framework that combines the strengths of two different classification methods, CNN and R.F.F., and two different segmentation methods, U-Net, to tackle the problem of brain tumor identification and categorization from MRI scans. Furthermore, the model's input is significantly improved during image preprocessing with the help of Median, Gaussian, and Wiener filters. The model validation was initiated by carefully analyzing the results from three federated clients, which gave satisfactory categorization metrics-95.52%. Although macro averages varied from 91.28% in Z_1 to 95.52%, the micro averages ranged from 91.26% to 95.51%, and the weighted averages ranged from 91.57% to 96.5571%. These results thus highlight the model's ability to obtain multiple versions of local datasets. The KPIs were outstanding when evaluated at the individual and team levels using federated averaging, a method combining local highlights to build a generic and robust model. This outcome univocally indicates an adequate conversion of the data of a given region into a viewpoint of the whole world, as the federated model achieves an initial accuracy of 97% for Z_1 and gradually increases to 99% for Z_6. An increasing accuracy curve demonstrates the model's ability to generalize from the theoretical knowledge of disparate sources. We propose using federated learning, CNN-RF models, dual U-Net segmentation, and an image filtering strategy for medical image analysis, which proves to be a completely viable and highly efficient solution. The statement puts federated learning under the spotlight to develop collaborative, privacy-preserving, and accurate diagnostic aids for sensing brain tumors. This starts a new epoch in the risk-free and suitable treatment of health care information.

AUTHORS' CONTRIBUTIONS

It is hereby acknowledged that all authors have accepted responsibility for the manuscript's content and consented to its submission. They have meticulously reviewed all results and unanimously approved the final version of the manuscript.

LIST OF ABBREVIATIONS

RF	=	Random forest
CNN	=	Convolutional Neural Network
LA	=	Left Atrium
MRI	=	Magnetic Resonance Imaging
GDPR	=	General Data Protection Regulation
HIPAA	=	Health Insurance Portability and Accountability Act

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

Not applicable.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The data and supportive information are available within the article.

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CONFLICT OF INTEREST

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