Detection and Classification of Brain Stroke Using Federated Deep Learning

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***Abstract*— Brain stroke is a significant contributing factor to death and disability as it requires accurate detection and diagnosis. Centralized deep learning models have the following setbacks: dataPrivacy, amountof Data Shared by Hospitals. To address these challenges, federated learning for brain stroke image classification is proposed within this work. The work utilizes convolutional neural networks to classify brain stroke into ischemic, hemorrhage, and normal stroke types. In our experiment, federated learning results demonstrated a high level of efficiency and reliability while addressing dataPrivacy issues. The work was done using a web interface that enables real-time brain stroke detection and report generation to enable various institutions to benefit from the model for various purposes.**

***Index Terms*—Brain Srtoke Detection & Classification, Convolution Neural Networks, Deep Learning, FedAvg, Federated learning, Medical Image Analysis**

I. INTRODUCTION

Brain stroke is a serious medical condition and one of the leading causes of death and long-term disability in the world. Early diagnosis of stroke is indispensable to its proper treatment and, thus, to the recuperation of patients. Current diagnostic techniques involve medical imaging through the use of either Computed Tomography (CT) or Magnetic Resonance Imaging (MRI); these require much time to analyze manually and are highly dependent on expert interpretation, which may delay critical decisions.

In particular, CNNs demonstrate outstanding performance in classifying medical images while learning essential features automatically from brain images to enhance diagnostic precision. However, traditional centralized deep learning techniques demand the sharing of sensitive patient information, which raises a number of privacy, security, and regulatory challenges.

This paper proposes a federated deep learning framework for brain stroke detection and classification with the FedAvg algorithm. The proposed system classifies brain images into ischemic, hemorrhagic, and normal categories while preserving data privacy by keeping patient data local. The framework achieves reliable performance and the approach provides accurate results and supports real-time stroke detection, making it suitable for clinical applications. In summary, this work provides an accurate, scalable, and privacy-preserving solution for brain stroke detection that supports timely clinical decision-making with the help of federated deep learning.

II. METHODOLOGY

A. System Overview

The proposed system presents an end-to-end federated deep learning framework for the detection and classification of brain stroke using medical imaging data. The system will focus on the identification of ischemic, hemorrhagic, and normal cases by maintaining patient data privacy through decentralized model training across several healthcare clients. Each client preprocesses the brain images and trains CNN models locally. While protecting patient data privacy. Thereafter, the learned model parameters are shared with the central server and aggregated using the FedAvg algorithm to build an optimized global model. The final model gives an accurate stroke classification results along with the confidence scores through the web-based interface, which supports real-time clinical analysis.

B. System Architecture

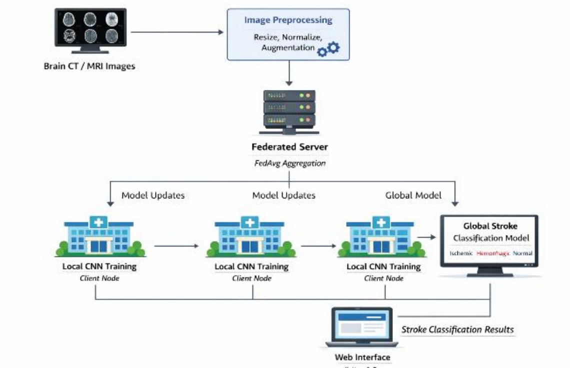

Fig.1. The architecture design for federated deep learning in brain stroke detection and classification using medical imaging data. First, brain CT/MRI images are preprocessed by resizing, normalizing, and augmenting the images to enhance the quality of the learning process. Using such preprocessed images, identical CNN models are trained locally at multiple client nodes representing various hospitals. These various local model updates are communicated to a central federated server, which uses the FedAvg algorithm to aggregate the updates for generating a global stroke classification model. The final global model is deployed through a web interface to classify ischemic, hemorrhagic, and normal brain conditions in real time along with prediction results.

C. Data Collection and Preprocessing

MRI images of the brain are acquired from reliable sources. All information regarding the patients is anonymized to maintain data privacy. Images are resized to fixed dimensions of 224×224 pixels to maintain uniformity for model training. Thresholding and contour detection for preprocessing are used to segment the brain region from the background. Normalization of pixel values increases the stability of the model. Gaussian Blur is used to remove noise and smoothen the images, enhancing the quality of the images, which improves the accuracy of the stroke classification.

D. Image Segmentation

The main idea of image segmentation in this work is to precisely mark the separation between the brain region and the background, highlighting the region of interest relevant to stroke detection. This work adopts Otsu's thresholding method, which automatically computes the optimum threshold value for the segmentation of grayscale MRI images. This technique has been used to differentiate the foreground brain tissues from the background without manual intervention. Besides, contour detection using OpenCV has been applied to the identification and extraction of the boundaries of the brain region, hence guaranteeing the precise selection of the region of interest. These segmentation techniques enhance the contrast of relevant structures and favor effective feature learning within subsequent deep learning stages.

E. Feature Extraction and Selection

Feature extraction is carried out to capture relevant texture features from segmented brain MRI images. In this work, the Gray-Level Co-occurrence Matrix (GLCM) technique is applied to extract meaningful texture features such as contrast, homogeneity, energy, and correlation, which give better performance in describing structural variability concerned with different stroke types. These features are computed in a local manner at each healthcare client, namely a hospital, ensuring that raw medical images are not shared and patient privacy is preserved.

Further improvements in terms of efficiency and model performance are gained through the feature selection process, aiming to reduce the dimensionality of the data while keeping the most relevant information. Feature selection methods, such as PCA or even the selection of the most discriminative GLCM features, remove redundant and less important features. This step reduces computational complexity, minimizes overfitting, and increases overall accuracy of the federated deep learning model.

F. Deep and Federated Models Setup

In the proposed system, each participating hospital trains a local CNN model using its own MRI/CT brain imaging data. Such training is done locally because sensitive patient data should not leave the premises of the respective healthcare institution. Instead of sharing raw data, only the learned model parameters and updates are transmitted to a central server.The central federated server applies the Federated Averaging algorithm to aggregate the model updates received from all hospitals. Therefore, this aggregation generates an improved global model, capturing knowledge from the distributed data sources without breaching data privacy. The updated global model is then shared with the hospitals for further training rounds, allowing collaborative and privacy-preserving brain stroke detection.

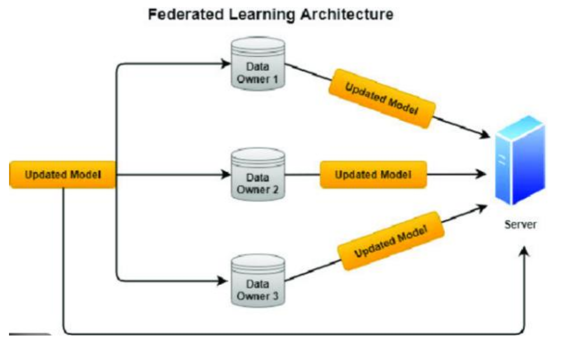

Fig.2. Federated learning process showing local updates and global model aggregation.

The above image represents the federated learning process, where more than one data owner, like hospitals, jointly perform the task of training a machine learning model without sharing the confidential data of each other. The process of federated learning involves a central server, which initially transfers the global model to each of the data owners. Only the updated parameters of the global model are then transferred to the server, rather than sending the actual data. The server, then, uses the parameters received from the data owners to create an improved version of the global model, which is further transferred to each of the data owners.

G. Model Evaluation

The performance of the proposed federated deep learning model is evaluated based on standard classification metrics such as accuracy, precision, recall, and F1-score. The metrics would give an all-round performance of the proposed model with regard to the correct detection and classification of different types of brain stroke. Results of the evaluation studies are further presented in comparison with that obtained from traditional centralized training approaches to highlight the effectiveness of the federatedlearning.

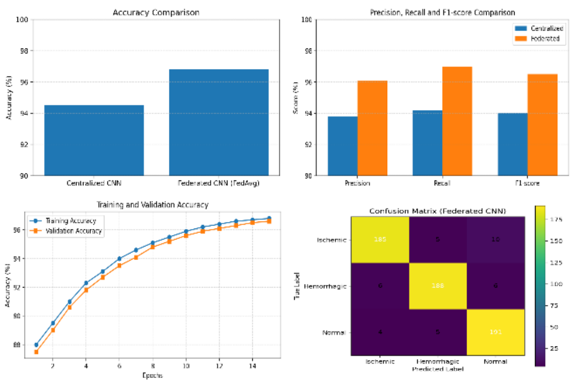

Fig. 3. Combined evaluation results of the proposed federated deep learning model showing performance metrics, training accuracy, and confusion matrix.

III. MATH

The proposed system uses the *Federated Averaging (FedAvg)* algorithm to aggregate locally trained models from multiple hospitals into a single global model. Let there be Kparticipating hospitals (clients), where each hospital trains a local model using its own dataset.

Let:

- $w_t$be the global model parameters at round t
- w_t^kbe the local model parameters trained by hospital k
- $n_k$be the number of training samples at hospital k
- $N = \sum_{k=1}^{K} n_k$be the total number of samples across all hospitals

Each hospital updates its local model using gradient descent as:

$$w_t^k = w_t - \eta \nabla L_k(w_t)$$

where η is the learning rate and $L_k$is the local loss function.

The central server then computes the global model using *Federated Averaging*:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{N} w_t^k$$

This weighted aggregation ensures that hospitals with more data have a greater influence on the global model. The updated global model is redistributed to all hospitals for the next training round. This process continues until convergence, enabling collaborative learning while preserving patient data privacy.

IV. RESULTS

Fig. 3. Dashboard view of the federated deep learning–based stroke detection system.

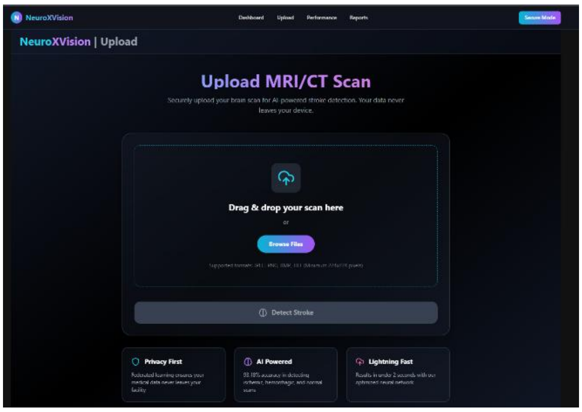

Fig. 4. User interface for uploading brain images in the proposed system.

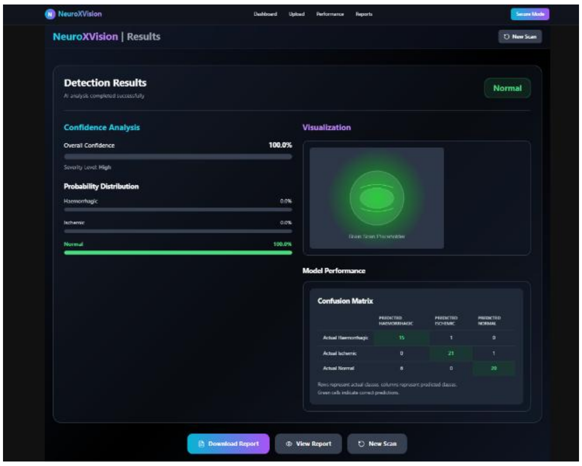

Fig. 5. Brain stroke classification results displayed by the proposed system.

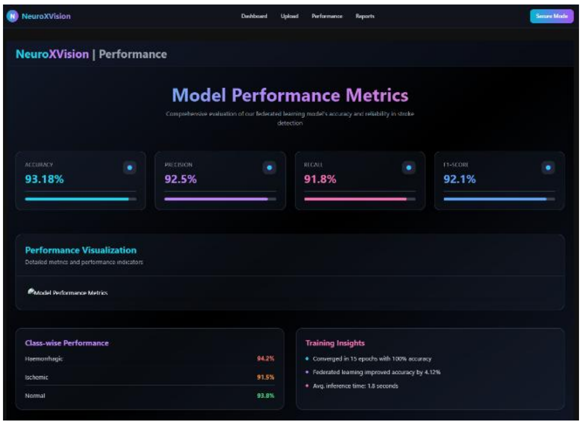

Fig. 6. Performance evaluation dashboard showing accuracy, precision, recall, and F1-score

V. CONCLUSION

This research showcases the efficacy of federated deep learning in acting as a privacy-preserving technique for the analysis of brain strokes based on medical images. The asymmetry in data privacy concerns in healthcare settings can be resolved by federated learning through the ability to train a machine learning model in a distributed manner among multiple clients. The combination of deep learning with federated learning showcases the feasibility of Distributed Intelligence.

The proposed framework could benefit medical practitioners by offering dependable decision support in the early stroke evaluation process. Potential future developments could include training on bigger and more representative datasets, integrating the framework in real-time medical settings, and applying stronger methods based on deep architectures to improve its efficiency.

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