Distributed brain tumor diagnosis using a federated learning environment

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ABSTRACT

In the last few years, a very huge development has occurred in medical techniques using artificial intelligence tools, especially in the diagnosis field. One of the essential things is brain tumor (BT) detection and diagnosis. This kind of disease needs an expert physician to decide on the treatment or surgical operation based on magnetic resonance imaging (MRI) images; therefore, the researchers focus on such kind of medical images analysis and understanding to help the specialist to make a decision. in this work, a new environment has been investigated based on the deep learning method and distributed federated learning (FL) algorithm. The proposed model has been evaluated based on cross-validation techniques using two different standard datasets, BT-small-2c, and BT-large-3c. The achieved classification accuracy was 0.82 and 0.96 consecutively. The proposed classification model provides an active and effective system for assessing BT classification with high reliability and accurate clinical findings.

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1. INTRODUCTION

Artificial intelligence (AI) is a branch of computer science that aims to make computers more intelligent and interactive [1]. It's a popular and exciting field of biomedical research and healthcare that focuses on issues that need to be overcome to develop AI applications such as clinical decision support systems in a real-world setting [2]. This medical data is multi-dimensional and variable-rich, and it was gathered from a variety of (sometimes incompatible) data platforms. It makes medical data, particularly images, difficult to analyze, and of significant interest for research [3]. Medical experts must put in a lot of time and effort to keep up with the tremendous expansion of medical image it works that is subjective, prone to human error, and can vary a lot from one expert to the next [4]. Medical imaging offers processes that provide visual information about the patient body [5]. Medical imaging aims to aid radiologists and clinicians in making the diagnostic and treatment process more efficient [6].

Machine learning (ML) is one of the AI branches that focus on a statistical model and algorithm that can perform a proper task without outright comments or instructions [7]; ML and deep learning have been widely used in the medical imaging domain [8], [9]. This work used a convolutional neural network (CNN) to diagnose a brain tumor (BT) disease in a federated environment [10]. One of the most common techniques and medical imaging can be used to detect and classify BTs in magnetic resonance imaging (MRI) images [11].

– Problem statement and contributions

In the case of a BT, early diagnosis, and detection may help the specialist evaluate the disease level and type of treatment, which saves the patient's life [12]. In this paper, the major problem is how we can implement an intelligent model able to detect BTs in a distributed environment. All the clinics and hospitals have their data, and these data are non-shareable because of the privacy issuers regarding the patients; therefore, the concept of federated learning (FL) and distributed system comes into the picture, where the training implemented locally at each client or hospital then only the training parameters are sharing between them without any share of patient's information [13]. The main contributions of this work are designing the CNN model for each client and exchanging the training parameters between clients and server. These parameters share using two models first one focuses on the average training method and the second technique focuses on the weight training ranking model. Each client has a rank and percentage of the training weight [14].

– Paper layout

This paper is organized as follows: in section two, the related work and the literature survey have been discussed and compared based on some metrics to find the main limitation of this work. Materials and methods are illustrated in detail in section three, and experimental results and analysis are explained in section four. And finally, the conclusion and features work have been shown in section five.

– Related work

Over the last years, ML and deep learning have been used in medical imaging papers because of their accuracy. In this section, we are reviewing articles closely related to our work. Furthermore, our study reveals that FL has a wide range of case studies. The researchers used "SU-net, " a FL model for BT segmentation based on the U-net architecture. "SU-net" combines the advantage inception module and a dense block to extract multi-scale features and reuse information from prior layers, improving information transfer and gradient flows. The proposed model achieved an accuracy of 99.7%, which are It was noticed more than a semantic segmentation DeepLabv^{3+} model and the classical model U-Net allocated to semantic segmentation health images [15], [16]. Kang Wei and his research team used a new framework based on "differential privacy" (DP). This method was used by adding artificial noises to parameters in the client direction only before aggregation, i.e., "noising before model aggregation FL" (NbAFL). First, the NbAFL can require meeting DP at different security levels by correctly adapting differences in added noises. Next, optimize the theoretical convergence related to the lack of function in the trained FL within NbAFL. The proposed method used a "K-client random scheduling strategy." It randomly chooses from N all clients to share for any aggregation. FL is a type of ML distributed its ability to prevent disclosing data clients' private data to enemies. However, evaluating uploaded parameters from clients can still reveal personal information [17].

The researchers suggested searching for an analytic solution within FL models or meta-analysis. In the federated setup, the model is controlled without sharing information across centres, only the parameters model. Instead, a meta-analysis performs a statistical test to combine results from several independent examinations. Different data sets it's stored in various institutions that cannot be directly shared because of legal concerns and privacy. As a result, the full exploitation of extensive data in the research of brain illnesses is limited. As a result, an entirely consistent framework in the federated analysis for distributed biological data was tested and validated [18].

Adnan Qayyum and his research team proposed a cooperative learning model for COVID-19 diagnosis by benefiting from a cluster FL method. These enabled remote healthcare centres to take advantage of each data in other places remotely without sharing the data. Despite substantial developments in modern years, cloud-based medical treatment applications are underutilized because their restrictions run hard privacy and protection (for example, low latency), and remote healthcare points lack diagnostic advanced facilities [19]. Felix Sattler and his research team used "sparse ternary compression (STC)" a modern compression system intended expressly to suit the request of FL surrounding. The expensive of privacy-preserving collaborative learning is a significant increase in communication overhead through training, which can decrease lot-required communication by several compression methods; however, in FL, these methods are bounded use by compressing communication upstream from clients to the server only or performing only well under idealistic conditions example id distribution in the data client, usually are rarely presented in FL [20]. Table 1 illustrates the comparison between the related work.

In previous works, the main limitations that suggested model suffering from the publishing of machine learning infeasible for many computing applications (high and expensive). In addition, it's costly were using peer-peer. In the proposed work, FL models are suggested to support BT classification efficiently. It protects patient dataset privacy and does not collect a central database on the server.

Table 1. Summary of related work (FL)

Reference	Datasets	Proposed techniques	Purpose	Accuracy (%)
[15]	Brain MRI segmentation	FL model using SU-Net	To solve the constraints of privacy protection regulations, sharing data directly between multiple institutions is prohibited.	99.7
[17]	MNIST dataset	Differential privacy	To process information that may be subject to adversaries by analyzing load parameters from customers.	-
[18]	multi-database (ADNI, PPMI, MIRIAD and UK Biobank)	Propose a FL framework for securely accessing and meta-analyzing biomedical data without sharing individual information.	To address different datasets stored at different institutions, which cannot always be shared directly due to privacy and legal concerns, thus limiting the full exploitation of big data in the study of brain disorders.	-
[20]	Chest X-ray and chest ultrasound images	Cluster FL	To overcome on restrictions hard privacy and protection in the cloud and to solve remote healthcare points lack diagnostic advanced facilities.	97
[21]	CIFAR-10 and MNIST dataset	STC, a new compression framework	To address the cost of a significant communication overhead during training in FL, its privacy-preserving collaborative learning.	-

2. MATERIALS AND METHOD

This section contains the proposed model phases based on manipulating the data used. Figure 1 shows the framework of the federated proposed model. Some of the processing has done in each client, starting from preprocessing, training the local model, and finally sharing the training weight with the global model in the cloud.

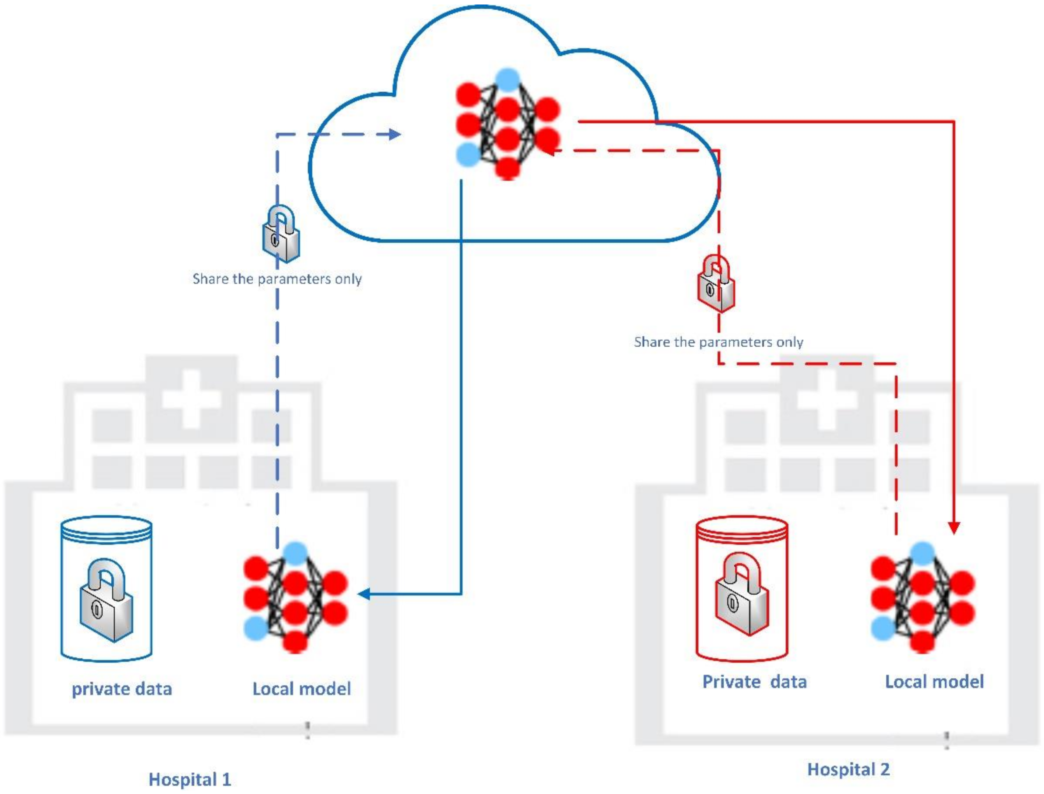


Figure 1. Structure of the proposed model using the FL environment

2.1. Preprocessing

Almost all of our brain MRI datasets have unwanted spaces and regions, which leads to poor classification performance [21]. This necessitates cropping images to remove unnecessary portions and focus on what is essential [22]. We used a method of cropping that involves extreme point calculations employed as shown in Figure 2. Before performing any post-processing, the raw MR pictures are loaded. After that, convert the MR images into grayscale, and blur it slightly by using gaussian bluer, then using a threshold to produce binary pictures [23]. In addition, we use dilation and erosion to reduce picture noise. After that, we chose the picture with the biggest contour and computed the images' four extreme points (the extremes at the top, bottom, right, and left) using just the threshold images. Finally, we use the contour and extreme points to crop the image [24]. Using bicubic interpolation, the tumor pictures that have been cropped are resized. As opposed to approaches like bilinear interpolation, which have a lot of noise at the borders, bicubic interpolation is preferable for MR pictures since it smooths out the curve more smoothly [25].

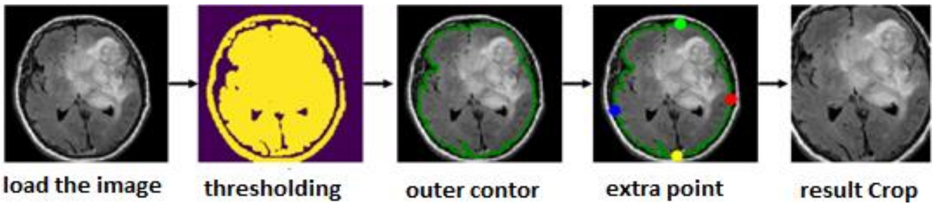


Figure 2. Preprocessing steps of MRI images

Because our MRI dataset was so small, we had to rely on image augmentation. Images can be augmented to produce an artificial dataset by altering the original dataset. Multiplication, rotation, repositioning, brightness, and other image attributes are only a few methods used to create many copies of the original [26]. According to the model's creators, classification accuracy may reportedly be increased by supplementing current data rather than acquiring new information. Our image augmentation process generated additional training sets using various augmentation procedures (rotation and horizontal flipping). The input is rotated by 90 degrees zero or more times at random as part of the data augmentation rotation procedure [27]. Each of the rotating pictures was also flipped horizontally. We recommend resizing all MR pictures in our dataset to the same width and height to achieve the best results [28]. The MR images are resized to (224×224) pixels in this study [29].

2.2. CNN model

Convolutional neural networks (CNNs) are a type of deep neural network that employs convolutional layers to filter inputs for meaningful information [30]. By connecting neurons to specific areas in the input, CNN's convolutional layers use these filters to compute the outputs of the neurons linked to those regions [31]. An image's spatial and temporal details can be gleaned with its aid [32]. A weight-sharing approach is applied to minimize the number of parameters in the convolutional layers of CNN [33], [34]. CNN is composed of three main components: to learn the temporal and spatial features of an image, a convolutional layer is used, followed by a subsampling (max-pooling) layer, and finally, a fully connected (FC) layer for classification [34], [35]. The central architecture of CNN is shown in Figure 3.

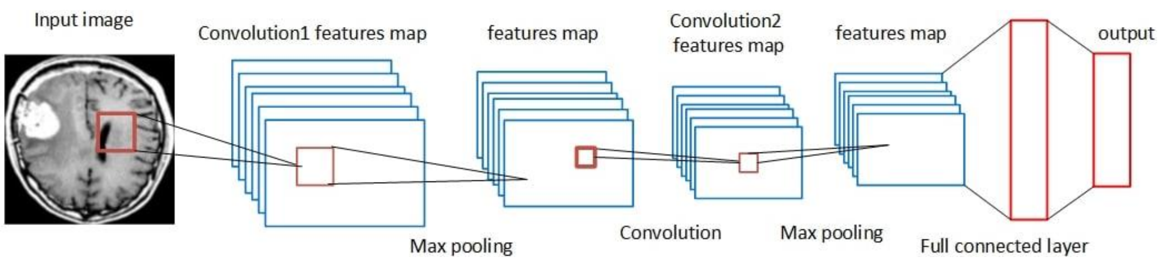


Figure 3. Proposed CNN's architecture layers

2.3. F ederated learning environment

Federated learning (FL) is a collaborative machine learning method that emerges promising solutions for protecting user privacy by allowing model training on a huge amount of decentralized data [34]. FL prefers to share models rather than share data. A typical FL model uses a novel training platform that keeps clients' data private locally while obtaining a high-performance global model [36]. Traditional machine learning methods assume the existence of central (cloud-based) organizations responsible for data processing [37]. Nonetheless, the complexity of accessing private data, along with the high cost of transmitting basic data to a central server, and due to ever-increasing data privacy concerns and network restrictions, data owners are frequently concerned about sharing their data with another party, whether it is a well-known business or one that they are unfamiliar with [38], [39]. Led the development of FL, a decentralized machine learning approach [40]. Algorithm 1 explain the FL work of the proposed model.

Algorithm 1 of brain tumor classification model in federated environment

```
Input MRI images
Output classification result
Algorithm Steps
Step1: Global CNN Model initialized in server.
Step2: Establish a number of clients =2 (in this paper).
Step3: Deploy the CNN to each client.
While communication _iteration < = max_number do
Client-side:
        1. Feature extraction using CNN model.
        2. Train the CNN model based on Features.
        3. From the fully connected layer, get the training result.
        4. Evaluate the performance based on the metrics
        5. Return the final weight to the server.
 Server-side:
```

$$Average\_weight = \frac{(\sum_{i=1}^{no\ of\ clinet} wi)}{no\ clinets}$$

```
Update the weight for all clients
End
Output training model for brain tumor classification
```

3. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental result has been implemented using python 3.8.8, TensorFlow 2.7.0, and Keras 4.3.0 tools. the specifications of the computer have been used is Core i7 10th generation, GTX 1650 Ti and 16G RAM. All the experimental result test it on two different datasets.

3.1. Dataset

A set of experiments is run on two publicly accessible MRI datasets for the categorization of BTs. To keep things simple, we referred to the first batch of brain MRI pictures as BT-small-2c, which contains (253) brain images retrieved from Kaggle [41]. It consists of 155 images of BTs, and the remaining 98 images are healthy. The BT detection 2020 dataset, which we've dubbed BT-large-3c, was also obtained from the Kaggle [42]. 3,264 brain MRI slices are included in the dataset. Meningioma, pituitary, and glioma are among the three types of tumors seen there, and no tumor. For meningioma, there are 937 pieces, 901 slices for the pituitary, 926 slices for the glioma tumor, and 500 no tumors. We have selected a subpart of the original dataset; MRI images contain two parts: 500 normal and healthy and 937 meningioma tumor images.

3.2. Result and environment

We utilize the same CNN networks for training and classification, regardless of whether learning is centralized or federated. In our experiment, we use two different models of deep learning, CNN convolution neuron network and pre-training visual geometry group (VGG-16), in the centralized learning for comparison with FL. Before any changes to the network parameters are made, the normal Adam optimizer is used to minimize the loss functions. When the local learning rate was set to 0.001, we used a batch size of 32 and 45 training epochs. All images are scaled to 224×224 pixels to preserve a similar structure.

In this study on FL for BT diagnosis, decentralized, and collaborative learning in a private data environment is an essential subject for our research. Training, validation, and testing were performed on three independent datasets. The training data is used to train the model, while the validation data is used to evaluate the model and adjust its parameters. In the end, we'll use the results of these tests to assess our model. BT-large-3c will be used to divide our data into training, validation, and testing. With a batch size of 32. We trained the models for 45 epochs. The FL model showed (97%) accuracy on our training data and (96%) accuracy on our validation dataset and showed (0.24%) loss on our data and (0.29%) validation loss. The accuracy graph of the testing and validation phase during the iterations of our suggested method is shown in Figure 4.

To evaluate the success of the proposed approach, a confusion matrix is utilized to illustrate the model's classification performance and reliability. The confusion matrix is used on both datasets that show the experiment's class-wise performance in Figure 5, this figure iullustrate confusion matrix of two different dataset

Figure 5(a) for (BT small -2c) and Figure 5(b) for (BT large-3c). This strategy can best appear category-wise accuracy of the presenter's approach in the concept of real and predicated category. Table 2 shows the comparison results based on performance measures, including F1-score, recall, precision, and accuracy obtained from the proposed CNN model, VGG-16, VGG-16 with the support vector machine (SVM) classifier and FL on two datasets.

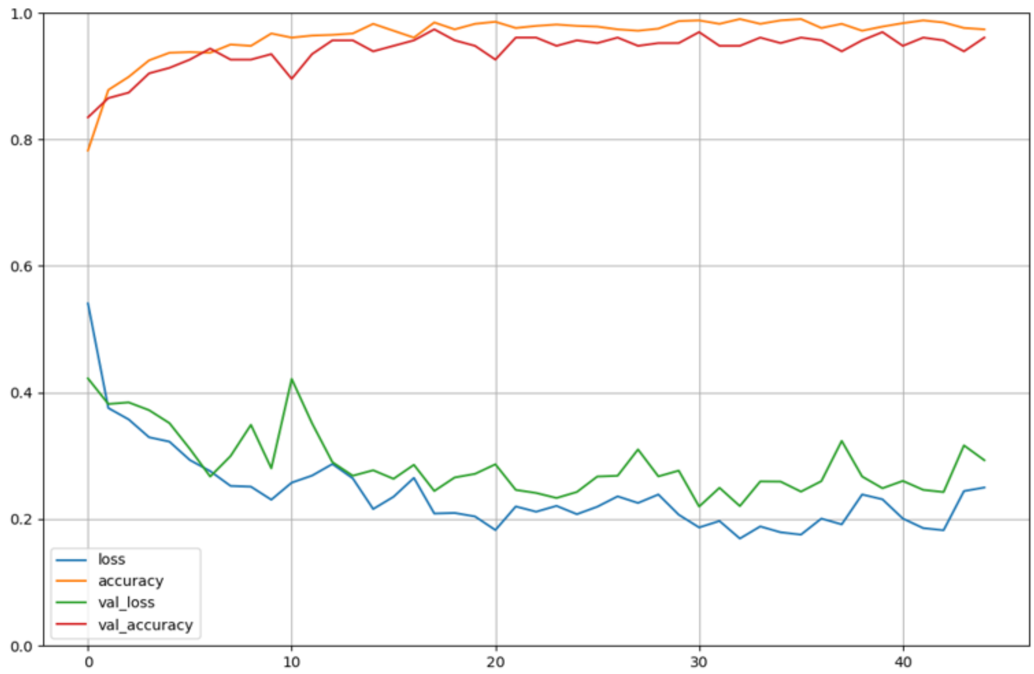
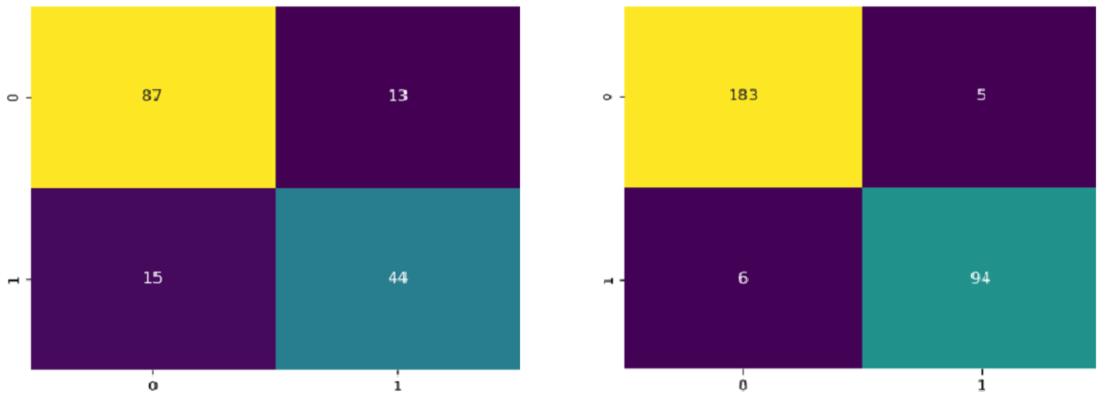


Figure 4. Training and loss function of the federated learning (BT-large-3c)



(a) (b)

Figure 5. Confusion matrix of two dataset (a) confusion matrix on BT-small-2c and (b) confusion matrix on BT-small-3c

Table 2. Comparing the result of the proposed model with different strategies

Dataset	BT-small-2c Performance Metric				BT-large-3c Performance Metric			
Model	Precision	Recall	F1 score	accuracy	Precision	Recall	F1 score	accuracy
Proposed CNN	0.85	0.89	0.87	0.83	0.95	0.97	.096	0.94
VGG-16	0.82	0.90	0.87	0.88	0.89	0.97	0.93	0.94
VGG-16 + SVM	0.85	0.41	0.55	0.72	0.74	0.97	0.85	0.81
CNN in FL Environment	0.82	0.85	0.87	0.82	0.97	0.97	0.97	0.96

3.3. Discussion and analysis

This section compares the outcomes of FL to those of a centralized strategy. We've examined how our FL-based approach performs in terms of precision. The comparison of CNN implementations between data-sharing and FL over our training dataset BT-large-3c. The accuracy ratings of the models are used to measure their quality in the (BT-large-3c) dataset. The recommended FL approach may produce a higher classification result without exchanging data with other clients, as demonstrated in Figure 6.

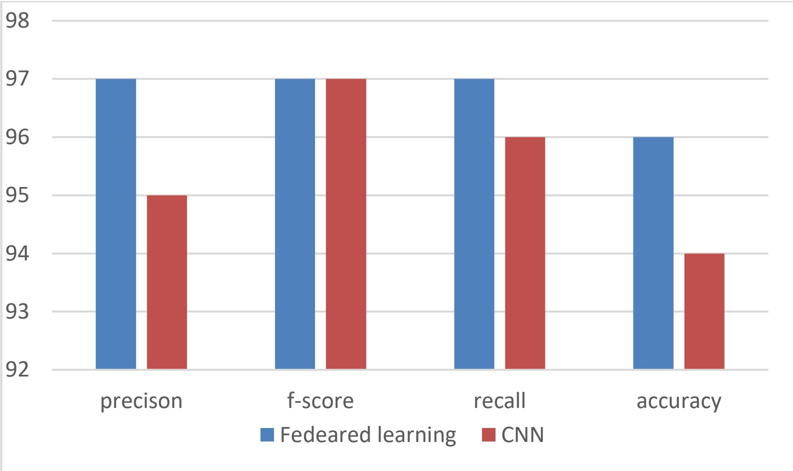


Figure 6. Accuracy CNN and federated learning (BT-large-3c)

4. CONCLUSION

In this paper, FL environments have been tested and evaluated for MRI image analysis and diagnosis of BTs. This study proposed a deep convolutional neural network-based FL framework to identify brain cancer in MRI images. There are several benefits to using this decentralized and collaborative platform, including the ability to transmit private medical data amongst clinicians throughout the world. An examination of two medical imaging machine learning methodologies based on CNNs was undertaken before moving on to the next level. These were essential for centralized learning and distributed FL. An experiment was conducted to compare the outcomes of FL against those of central learning. Through FL, it is feasible to link all of the fragmented medical institutions, hospitals, and equipment while ensuring the privacy of all participants by working together; researchers will be able to detect brain cancers much more quickly and accurately.

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