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BrainCrossFed CNN Model for Alzheimer Classification using MRI data and Comparison and Benchmarking proposed model with DINOv2 and ExplainableAI using GradCAM

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Abstract—**Alzheimer is one of the key mental illnesses suffered by 55 million people worldwide and 10 million new patients are added every year. If Alzheimer's is detected in early stage, then the impact of disease will be reduced. Artificial intelligence (AI) models are helping in early diagnosis using MRI images. For better AI model development, the model needs to be trained over a huge dataset. But Health data privacy is another key concern of data collection, and hence federated learning framework helps models get trained over data without data transferring to cloud platform. Other Key concerns of AI model development is the availability of labeled data and benchmarking the model performance developed on dataset, which is trimmed or is a modified version. As availability of research work on specific data is rare. Currently, researchers have to develop other research models for specific data and such approaches take more time. Also, doctors expect explainability of the model, instead of black box model. Proposed BrainCrossFed model addresses data privacy concerns by avoiding the need for data transfer to cloud and leverage available labeled data at different federated nodes along with a dataset for Alzheimer to compute cross fed average of model weights. Due to the proposed Cross Fed Avg algorithm performance of the proposed deep learning model accuracy is increased from 99.11% to 99.77% close to 100%. Also such cross fed average enables the model to find global minima. Final performance achieved by the proposed model is 99.77%, with 100%. The performance of the model is benchmarked with current well known classification models, State-of-the-Art (SOTA), self supervised models like DINOv2[1], for the same datasets. DINOv2 model has achieved 98%. Other generic well known models like ResNet101, DenseNet121, and Visual Geometry Group16 (VGG16) and customer models[2] have achieved max performance 97.60%. The GradCAM developed to explain the classification result.**

Keywords— Federated Learning, FedAvg, Self Supervised Models, DINOv2, GradCAM, BrainCrossFed, Alzheimer, MRI

I. INTRODUCTION

Alzheimer is one of key medical diseases impacting the whole world economically and also personal life. Currently more than 55 million people across the world are impacted by Alzheimer and every year 10 million more people are getting added to this list. The disease impacts family also as people with Alzheimer start forgetting things and managing such patients in home need dedicated support. So overall economic impact will be in trillion dollars. The disease can be effectively managed, if detected in an early stage, hence identifying AD in early stage is crucial.

There are several ways of diagnosing and classifying disease stage. Voice sample, symptoms, language test, Magnetic Resonance Imaging (MRI) and other medical tests. Most prominent way of testing is based on brain MRI scanning. Firstly MRI scans are costly and doctors who analyse and diagnose will be less as compared to the population of developing countries, where such disease is spreading very fast. Solutions like an AI model for diagnosing and detecting the stage of Alzheimer will be helpful for mankind.

Building an effective AI model to determine Alzheimer disease stage needs large datasets and large cloud computation to train over such large data. The key concern here is two fold, firstly data privacy concern, collecting data from multiple patients and transferring to cloud platform, violating data privacy law across the world. Secondly, availability of label data to train the model.

Another concern for AI researchers is evaluating the model developed for a specific dataset. As the dataset available at public websites like Kaggle and Github etc will be modified datasets of original dataset created. To compare the performance of a developed model with other models for a specific dataset, it will be difficult to find such research papers. The data set will be trimmed versions of original data. So researchers have to develop several models to just bench mark the proposed model with other models proposed by other papers. This approach will be time consuming and also depends on how the model is developed to test performance over specified data. Another approach is to develop the well known models, State-of-the-Art(SOTA), or other proper models tested over other dataset, where such models performed well. Developing such models will be less time consuming and better benchmarking on performance. As these models, which perform well over several datasets will perform better on most datasets. Few common well known classification models are VGG, ResNet50 and so on. Also self supervised models, large models like DINOv2 and others are better models to bench mark.

AI models in healthcare diagnosis will have to explain the diagnosis using explainable AI techniques, as human health diagnosis is critical activity. Wrong diagnosis will harm human health, so doctors will suspect the black box nature of AI models. Hence Explainability of model development is essential. Developing what kind of explainable model, depends on data type like text data, tabular data, image data, audio data etc used for training the model and what kind model developed like machine learning, deep learning, natural language processing etc for dataset. Also it depends on problem types like classification model, regression model, segmentation model and so on. Depending on all mentioned information, the right explainable AI model has to be selected. For deep learning, classification models, for Alzheimer disease classification, which depends on specific patterns on MRI images, GradCAM suits well.

Second session following the introduction covers the literature review, the third section covers the research methodology and proposed architecture in detail. Fourth section covers the result of the proposed model and benchmarking the result with other well known models. Finally conclusion with future scope.

II. LITERATURE REVIEW

There exist several AI papers building models for diagnosing Alzheimer. Literatures looked into are focused on Alzheimer, MRI data based Alzheimer diagnosis models, Federated learning, explainable AI, and well known classification models.

The research work focuses on building MRI data based Alzheimer disease stage diagnosis. The paper[3], proposes an ensemble model for ADNI Dataset and classify Alzheimer Disease(AD) and normal, binary classification and performance achieved is 94% with mean accuracy 88%. The paper[4] uses deep learning(ResNet50) as feature extraction from MRI images and finally uses machine learning(SVM, or RF) to classify the data. The accuracy achieved is,ResNet50 with 99%, ResNet + SVM: 92%. The paper[5], shows leveraging available other data for fine tuning models to get better performance. Leverage MRI images to fine-tune models for X-ray image based lung disease classification. The paper influences the decision to use two different but similar kinds of images, MRI images to tune the proposed model. The paper [6], leverages autoML for benchmarking the model developed for datasets, for which finding reference models available to compare the performance. This paper influences, leveraging well known AI models to benchmark the performance of developed models. The well known models used to compare are VGG, as the paper [8] achieved performance VGG16- 96.39% VGG19-96.81% for AD stage classification, ResNet50 - the paper[9], achieves 98.99%, and new advance model DINOV2[1]. Overall VGG, ResNet and DINOv2 model used for benchmarking the performance of proposed model. The paper[7] does exploration of explaining AI models for MRI dataset. Most papers use GradCAM, as it provides insight about part of the image influenced decision with colour code and each to understand.

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III. RESEARCH METHODOLOGY

The research methodology consists of a few stages,

Stage 1. Selection of datasets.

Two kinds of datasets selected for the experiment, one MRI labeled data for Alzheimer disease stage classification and other MRI labeled data used to fine tune performance of proposed model. The objective is, in the real world, a large quantity of unlabelled data available and small quality of labeled data available. So leveraging other labeled data along with datasets for defined problems is one way of addressing data concern.

Stage 2. *Federated Learning Experimental setup for crossFed framework.*

Setting up the federated transfer learning framework with two nodes and having different datasets at each node. The cloud server, where proposed Federated model weight aggravation called BrainCrossFed average algorithm works.

Stage 3: *Proposed CNN model developed and trained over federated framework*

Develop and customise the CNN model and fine tune the model, as per BrainCrossFed average algorithm.

Stage 4: Benchmark the model performance with other well known models

Select the well known Deep learning classification and train and test over the same dataset for benchmarking the proposed model.

A. Stage1: Datasets

Two datasets are selected. First Dataset is MRI Images with labels for Alzheimer disease stage. Research aims to leverage available other labeled data to compensate for small labeled expected data.

ALZHEIMERS DATASET

Kaggle Dataset, balanced Datasets using GAN model of generation. The original data consists data of four classes,

I. ALZHEIMER'S DATASET TABLE

Class	Patient	Training Images (balanced)	Testing Images
No Impairment	100	2560	640
Very Mild Impairment	70	2560	448
Mild Impairment	28	2560	179
Moderate Impairment	2	2560	12

Each brain image from the patient sliced horizontal axis around 32 sliced images. The MRI images are acquired with T1 weighted sequence. All the images are pre-processed by removing the skull and resized 128 X128 .jpg image.

BRAIN TUMOR DATASET (Add on Dataset)

II. ALZHEIMER'S DATASET TABLE

Tumor Type	No of Images (Training)	No of Images (Testing)
Glioma Tumor	826	100
Meningioma Tumor	822	115
No Tumor	395	105
Pituitary Tumor	827	74

B. *Stage 2 : Federated Learning Experimental setup*

Federated Transfer learning framework with two federated learning nodes and one service is virtually set up. The server, the MRIBrainCrossFed algorithm runs. BrainCrossFed algorithm consists of below three models.

1. Cross Fed Average Algorithm will compute the weights of the same model trained over two different datasets.
2. FineTuning Algorithm: The model weights calculated using BrainCrossFed average method then send the computed weights to each FL node for further training of the model for Fine tuning. This process will continue till the model performance over proposed data either keeps increasing or till patient iteration count does not expire.
    a. The patient iteration will be less than 10 if the model performance is above 90% and patient iteration will be more as the model performance is low.
    b. The objective of patient iteration is to minimise the network communication load over the network.
3. Benchmarking Algorithm: The algorithm picks up available AI models and sends them one by one to the FL node so that model will be trained and send the model performance. Create List of Model Name and performance over the actual data and will be used will also indicate further Fine Tuning of proposed model essential or not.

One FL node here represents a hospital or bigger institute having health data collected at the centre and data labeled. Actually here we used Kaggle available data, but in real situation, this data will be health data collected at the hospital centre. Another FL node represents other hospitals with other health data. Here, MRI based Brain tumour labeled data.

C. *Stage3: Model and Proposed architecture*

As the model sends to the FL node and gets trained as mentioned in proposed architecture, figure 1, the data privacy issue is addressed here. As the data never leave the FL node. Only proposed deep learning Model, Other benchmark models, Model weights and performance values transferred between FL node and FL service as shown in above diagram.

Also the proposed algorithm, MRIBrainCrossFed algorithm, leverages other label data available across several FL nodes, to improve the performance and runs at FL server. In this way proposed methods address the concern of not availability of large label data and also efficiently leverage other labeled data. The Benchmarking algorithm kicks in after model training concluded by the MRIBrainCrossFed algorithm. One by one well known models will be sent to the FL node 1 and trained over local data. Benchmark model restarts MRIBrainCrossFed algorithm for further tuning of model, if the proposed model performance of AD stage classification is lesser than the benchmarking model performance. The process iterated a few times, and will be terminated after achieving proposed model performance better than well known models or maximum attempt configured exhausted.

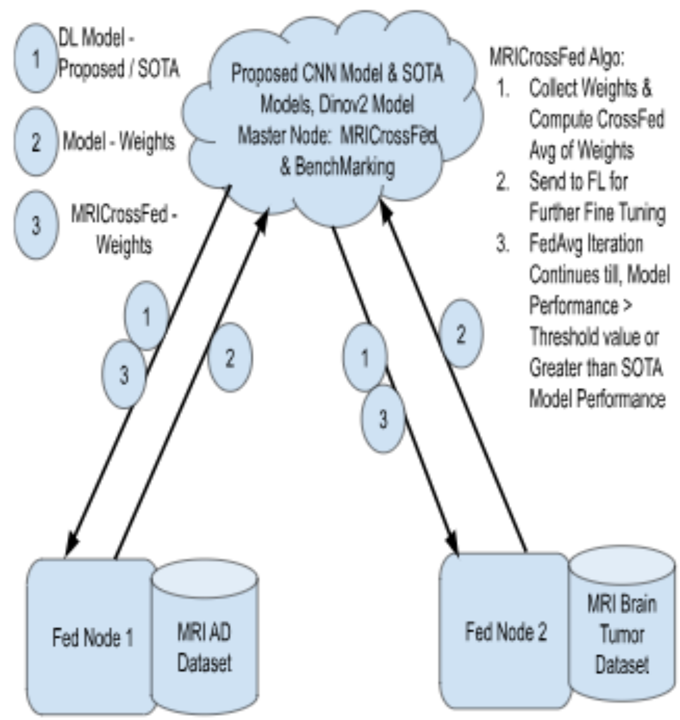


Figure 1: Proposed MRICrossFed Architecture

The well known models tested are Visual Geometry Group(VGG), VGG16, VGG19, ResNet50 and other ResNet alternatives. A Self supervised based Transformer model called DINOv2[1], from a Meta research team.

Proposed CNN Model & Parameters

The proposed CNN sequential model consists of 30 layers including 10 2D Convolution Layers, 5 Max Pooling years, 7 ***BatchNormalization*** Layers, 4 Dropout layers, 4 Dense layers including the last classification layers, as mentioned in the diagram below figure 2.

Architecture consists of 5 Blocks with each block consists of two Convolution layers followed by MaxPooling layer and followed by Fatten layer, then Dense layers and DropOut Layers. Activation Function used in **LeakyRelu** and Same Padding is used. Final classification layer activation function is **softmax** with 4 classes. Kernels in each block are in binary pattern as 16, 32, 64, 128 and 256. Model's Total params: 3,355,348 including Trainable params: 3,352,980

Model input is an RGB image(MRI image) of size 128 X 128 pixels. The input image is resized to 128 X128 and then normalised. Model is compiled with Adam optimiser and **CategoricalCrossentropy**() as loss function, with model evaluation metrics- accuracy & F1 Score. Model is trained over data for 200 Epoch with 32

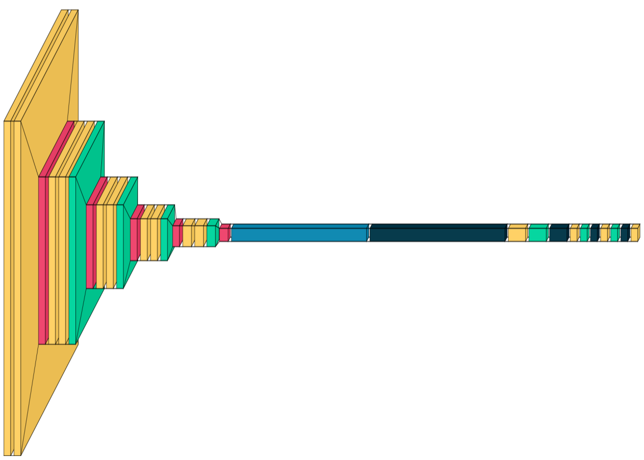


Figure2: Proposed CNN Model for AD Stage Classification

D. Stage 4: Benchmark the model performance with other well known models

Benchmarking models are selected based on literature surveys about well known classification models performance on MRI image and current well known models. These models keep adding to the list of benchmarking models, as new models proposed.

DINOv2 (DIscriminative NOise Contrastive Learning V2), introduced by Meta Research in April 2023, is a self-supervised approach for training computer vision models. Self Supervised learning models are well known models to leverage unlabelled data and labeled data to improve the performance. Vision Transformers are other models performing well on classification dataset. The DINOV2 is a combination of Vision Transformer with a self supervised Learning model. The model is used not just classification, but also instance segmentation, depth estimation, instance retrieval, and dense/sparse matching activities.

The pertained DINOV2 model is used here with weights of a large Vision Transformer called ***dinov2_vitl14***. The preprocessing of images is done using the MinMaxScaler method. Multiple patches of images created for vision transformers of horizontal and vertical size equal to 520 / ***dinov2_vitl14.patch_size***. The number of features created are 1024. Also other image preprocessing like resize image to 520 X 520 and cropping the centre image of size 518X518 so that 37 patches created and finally image normalisation with mean = 0.5 and standard division =0.2

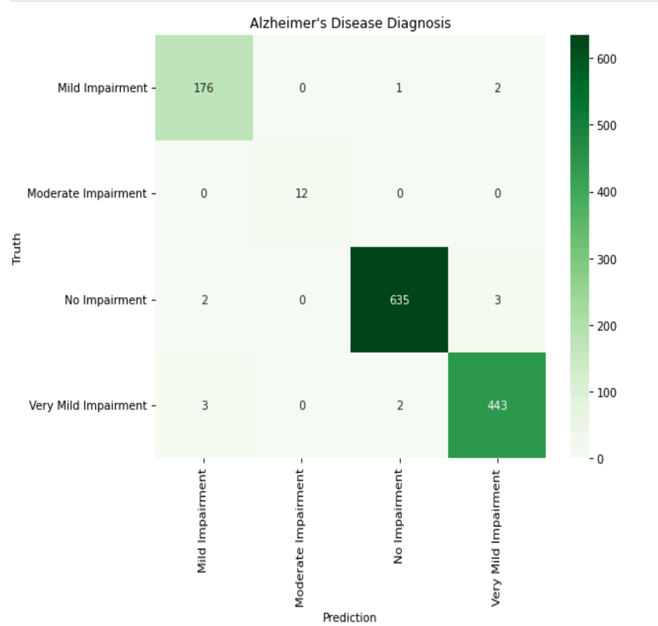
The proposed Modified DINOV2 model consists of Top layers as ***dinov2_vitl14*** followed by 4 linear layers, as the final linear layer is classification layer. The ***dinov2_vitl14*** works are feature extraction modules which extract 1024 key features from images, which will be fed sequentially to classification layers. AutoEncode Classification layers consist of 256 Neurone, followed by 128 and finally 256. The last layer is a classification layer with 4 output neurone. The DINOV2 model is compiled with Adam as optimiser and CrossEntropyLoss as loss function and Accuracy and F1 score as evaluation matrix.

IV. Result, Benchmarking & Explainable AI

The Proposed Model without BrainCrossFed achieves Balanced Accuracy Score: 99.11 % and other scores and Confusion Matrix as follows

A. Confusion Matrix of Model without MRIBrainCrossFed

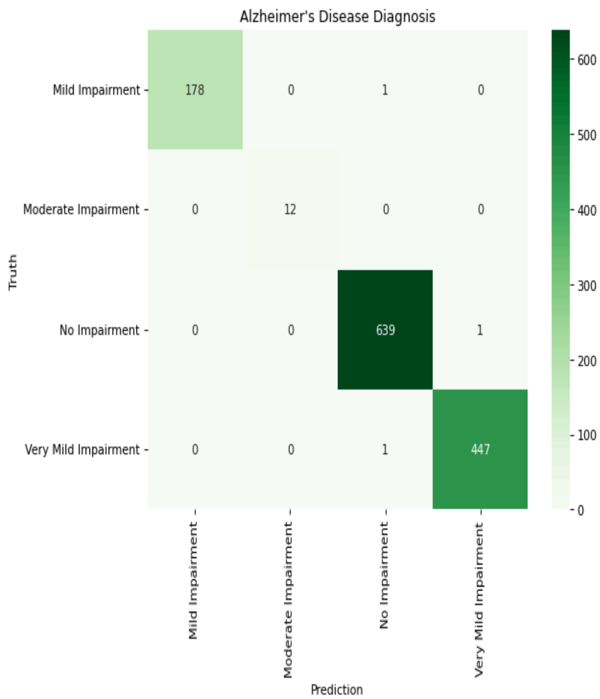
	precision	recall	f1-score	support
Mild Impairment	0.97	0.98	0.98	179
Moderate Impairment	1.00	1.00	1.00	12
No Impairment	1.00	0.99	0.99	640
Very Mild Impairment	0.99	0.99	0.99	448
accuracy			0.99	1279
macro avg	0.99	0.99	0.99	1279
weighted avg	0.99	0.99	0.99	1279



The Proposed Model with MRIBrainCrossFed model - accuracy achieved is 99.77% close to 100%. Confusion matrix and other matrix as follows

B. *Confusion Matrix of Model withMRIBrainCrossFed*

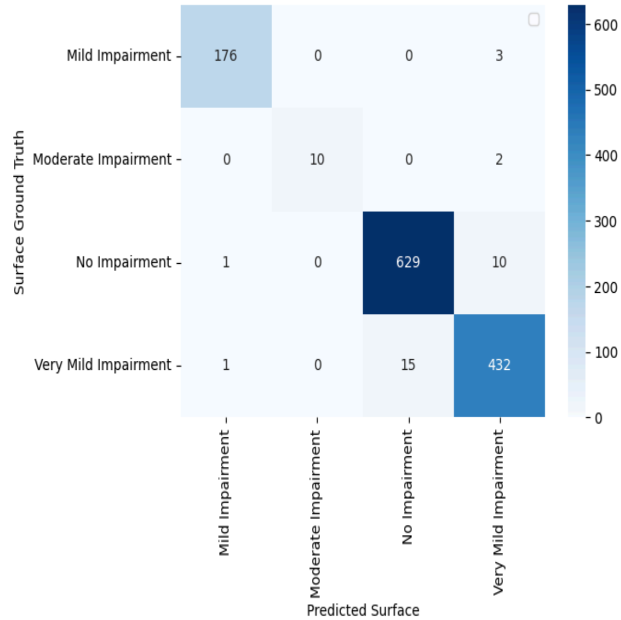
	precision	recall	f1-score	support
Mild Impairment	1.00	0.99	1.00	179
Moderate Impairment	1.00	1.00	1.00	12
No Impairment	1.00	1.00	1.00	640
Very Mild Impairment	1.00	1.00	1.00	448
accuracy			1.00	1279
macro avg	1.00	1.00	1.00	1279
weighted avg	1.00	1.00	1.00	1279



C. *DINOV2 - AdaDelta, accuracies achieved is 97%*

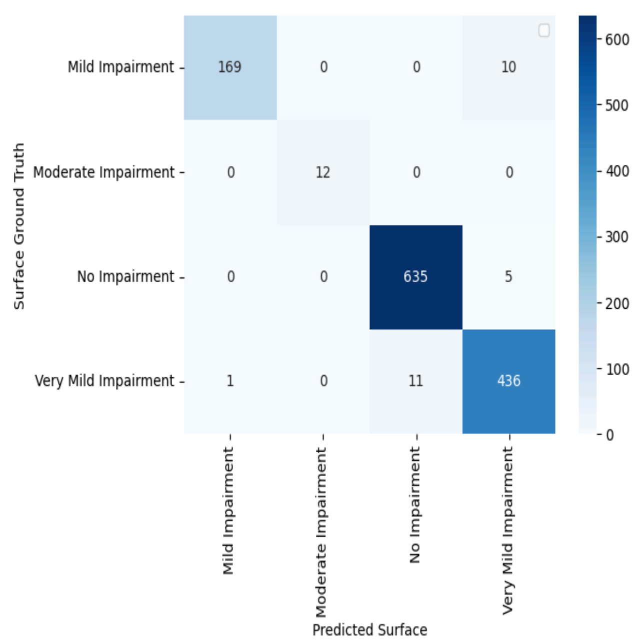
DINOV2 model used for bench marking and model customised to make model works effectively for AD dataset

	precision	recall	f1-score	support
Mild Impairment	0.99	0.98	0.99	179
Moderate Impairment	1.00	0.83	0.91	12
No Impairment	0.98	0.98	0.98	640
Very Mild Impairment	0.97	0.96	0.97	448
accuracy			0.97	1279
macro avg	0.98	0.94	0.96	1279
weighted avg	0.98	0.97	0.97	1279



D. *DINVO2 - Adagrad, accuracies achieved is 98%*

	precision	recall	f1-score	support
Mild Impairment	0.99	0.94	0.97	179
Moderate Impairment	1.00	1.00	1.00	12
No Impairment	0.98	0.99	0.99	640
Very Mild Impairment	0.97	0.97	0.97	448
accuracy			0.98	1279
macro avg	0.99	0.98	0.98	1279
weighted avg	0.98	0.98	0.98	1279



III. Overall Performance BenchMarking

Model	Accuracy	F1 Score	Precision / Recall
VGG16 [8]	96.39%	-	-
VGG19 [8]	96.81%	-	-
ResNet50[9]	98.99%	-	-
DINOV2 -AdaDelta	97%	96%	98% / 94%
DINVO2 - Adagrad	98%	98%	99% / 98%
Proposed Model	99.11%	99 %	99% / 99%
Proposed Model + MRIBrainCrossFed	99.77%	100%	100%/100%

Result indicates that the MRIBrainCrossFed model avoids overfitting and is able to learn effective ways and hence performance improves close to 100%.

E. *Explainable AI*

To explain the classification result, GradCAM at last Convolution layer of Proposed model with MRIBrainCrossFed as mentioned below

Figure 3: GradCAM based Explainable AI for Proposed Model

V. Conclusion and future scope

Alzheimer is one of key mental concerns impacting the world health and economy and is curable, if detected early. AI models help detect disease and stage early. But AI model development faces several key issues, data privacy concern, non availability of large labeled data. Another concern is how to compare the performance of a model with other models, as the dataset and environment will not be the same to get a better comparison. The paper proposes, MRIBrainCrossFed algorithm leverages Average of Model weights trained over different data, Transfer learning method and Fine tuning algorithm. Also proposed CNN model trained over Federated learning approach provides better performance 99.77%. It improves performance from 99.11% and also helps models overcome overfitting the model performance. MRIBrainCrossFed also helps to leverage other labeled data, to overcome concern of label data availability. The federated learning mechanism of model learning addresses other concerns of data privacy. Model benchmarking algorithms address concerns of effectively comparing the model performance. Using current well known models to benchmarking provide better ways of benchmarking. Healthcare models should not be black box, as doctors are keen to understand how the model predicts class/stage of disease. GradCAM provides insights about area or zone of brain image impacting in predicting stage of disease.

The Score enhances the performance further and also benchmark with other Well Known classification algorithms. To enhance performance the proposed model uses more FL nodes with other MRI labeled dataset. Another scope of enhancement is explainable the result effectively using another approach.

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