

MediFusionNet: A Hybrid CNN-Based Multi-Disease Diagnostic Web Platform

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Abstract

Disease diagnosis using medical images has become an indispensable part of healthcare today. This necessitates the development of smart and effective models. This research work proposes a MediFusionNet, a hybrid web-based CNN diagnostic tool for multi-disease diagnosis based on feature fusion between VGG16 and MobileNetV2 to enhance the classification performance for different medical imaging techniques. The proposed framework diagnoses Brain Tumors, Breast Cancer, Chest Diseases, and Lung Abnormalities from Brain MRI, Breast Ultrasound, Chest X-ray, and Lung CT datasets respectively. We apply a preprocessing phase, which consists of images' resizing, normalization, and augmentation to make the model robust. Federated learning technique is applied to train the proposed model while keeping patients' privacy intact during collaborative model training by not sharing any patient's data. The proposed model is trained and tested on the aforementioned datasets and is deployed in a web-based clinical platform for disease diagnosis, prediction, and report generation.

Keywords: Medical Image Analysis, Deep Learning, Hybrid Convolutional Neural Network (CNN), Feature Fusion, Federated Learning, Multi-Disease Diagnosis, Web-Based Clinical Decision Support.

1. Introduction

Medicine imaging serves as a major technique for the early detection of various diseases and also helps in the diagnosis through visualization of the inner body structures. Various imaging methods like Brain MRI, Breast Ultrasound, Chest X-ray, and Lung CT have been used

for diagnosing brain-related diseases, breast cancer, pneumonia, and lung cancer respectively. But manual analysis of images is both time-consuming and may involve human errors, and hence there is a requirement for intelligent computer-based diagnostic tools.

The recent development in the field of DL, especially CNN, has made considerable progress in the area of medical image classification through automatic feature extraction from the complicated image dataset [1]-[10]. However, most of the developed models only focus on one particular disease or one imaging modality. Furthermore, the process of centralized training of such models poses a threat to the privacy of patient data.

To address these challenges, MediFusionNet is introduced in this research as a combination of deep learning techniques for developing a multi-disease diagnostic system based on CNN, using VGG16 and MobileNetV2 in order to perform feature fusion and disease classification on four different medical imaging modalities. Our work introduces the concept of Federated Learning in developing this platform.

2. Literature Review

Deep Learning (DL) has emerged as an extensively used technique in medical image processing due to its capability to automatically discover discriminative features, thereby improving disease classification accuracy. The combination of hybrid CNN architecture and feature fusion has been proven to be quite effective in brain tumor classification because of improved feature extraction and model robustness [1] further, feature selection and parameter tuning have been used to increase the efficiency of disease classification [2]. Multimodal CNN architecture has been successfully used for brain tumor grading based on image features [3].

Transfer learning and federated learning have been widely studied for diagnosing breast cancer and analyzing medical images privately, where collaboration can be achieved while not compromising patient privacy [4], [5], [6]. In terms of identifying skin diseases, advanced lightweight CNN models have demonstrated a good trade-off between efficient computations and accurate diagnoses, where MobileNetV2 is one of the efficient backbones for such purposes [7], [8]. Besides, CNN models have proven to be quite effective in detecting COVID-19 infection and classifying lung nodules in chest X-rays [9], [10].

However, even though these researches have yielded promising results for individual

diseases, majority of the existing studies consider only one task at a time while constructing their model for diagnosis of each specific disease individually. There has not been much research done in terms of designing a unified web-based diagnostic system which can simultaneously perform multi-disease diagnosis by considering only one deep learning model at once. With this aim in mind, the proposed MediFusionNet has been designed to design a multi-disease diagnostic web-based system by combining the two aforementioned features of disease feature extraction along with unified inference.

3. Proposed Methodology

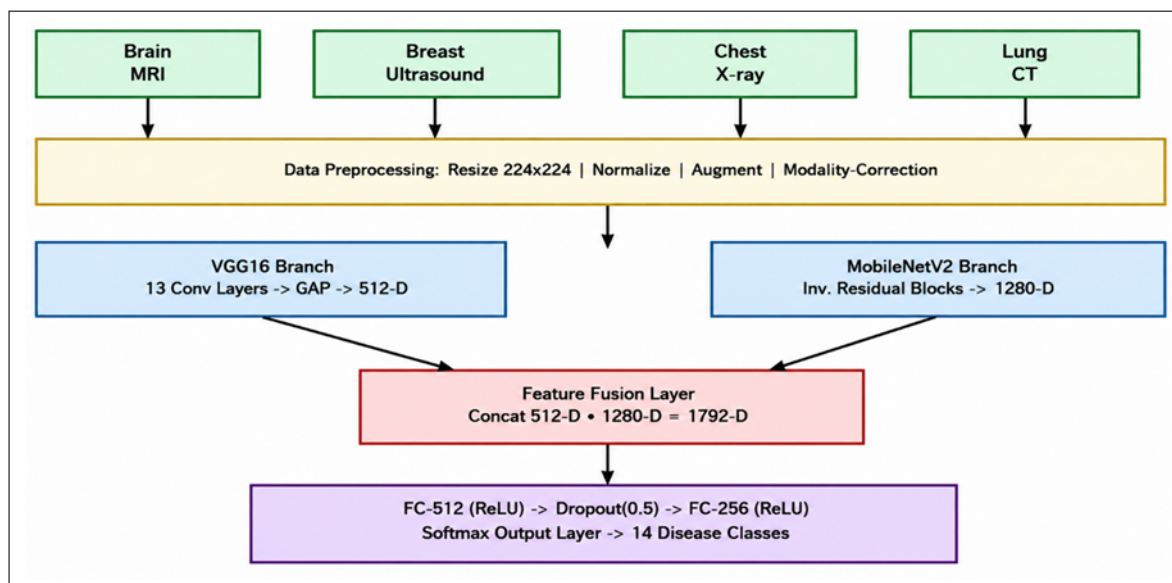


Figure 1. Architecture of the proposed MediFusionNet.

The workflow of the proposed framework is depicted in Figure 1. The structure of the MediFusionNet architecture includes six consecutive steps: data acquisition, data preprocessing, deep feature extraction using the CNN hybrid model, feature fusion and classification, Federated Learning, and web-based deployment. First, medical images from four freely available datasets are acquired and preprocessed. After preprocessing, the images are input to VGG16 and MobileNetV2 models to extract their deep features. These features are then fused and used to classify 12 distinct disease classes of four datasets including four brain tumor diseases (glioma, meningioma, pituitary tumor, and no tumor) [11], three breast ultrasound diseases (benign, malignant, and normal) [12], two chest X-ray diseases (normal and pneumonia) [13], and three lung CT diseases (normal, benign, and malignant) [14]. The federated learning technique makes

possible joint training of the model without violating patient's privacy. Finally, the trained model is deployed using a web platform for real-time disease detection.

3.1 Dataset Description

The proposed framework MediFusionNet uses four publicly available medical imaging datasets for multidisease diagnosis. The Brain Tumor MRI dataset has four classes including glioma, meningioma, pituitary tumor, and no tumor [11]. The BUSI dataset has three classes that include benign, malignant, and normal [12]. The Chest X-ray Pneumonia dataset has two classes, namely normal and pneumonia [13]. The IQ-OTH/NCCD Lung CT dataset has three classes including normal, benign, and malignant [14]. Hence, the total number of dataset specific diagnostic classes in combined dataset is equal to 12. All images are rescaled to 224×224 pixels before training, and normalized with stratified division to 70% training, 15% validation, and 15% test sets.

Table 1. Dataset description and experimental configuration

Dataset	Modality	Diagnostic Task	Classes	Split Ratio	Input Size
Brain Tumor MRI Dataset	Brain MRI	Brain Tumor Classification	4	70:15:15	224×224
BUSI Dataset	Breast Ultrasound	Breast Cancer Classification	3	70:15:15	224×224
Chest X-ray Pneumonia Dataset	Chest X-ray	Pneumonia Classification	2	70:15:15	224×224
IQ-OTH/NCCD Lung CT Dataset	Lung CT	Lung Cancer Classification	3	70:15:15	224×224

3.2 Data Preprocessing

The proposed MediFusionNet architecture includes the four modalities of medical imaging, and therefore needs a single preprocessing step to reduce variation in terms of image resolution, intensity, and quality. This phase ensures standardization of the input data, as well as preservation of clinically important features in the proposed technical system.

All the images are first resized to 224×224 pixels and normalized. The images are then processed with data augmentation by randomly rotating, flipping horizontally, zooming, and translating them. Furthermore, there is also modality-based preprocessing done in order to

minimize imaging artifacts without compromising disease-based attributes of images. These preprocessed images are then inputted into the hybrid CNN feature extraction module for deep learning.

The image normalization process is expressed as

$$I_{\text{norm}} = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \quad (1)$$

where I denotes the original pixel intensity, $I_{\min}$ and $I_{\max}$ represent the minimum and maximum intensity values, and I_{norm} is the normalized image.

3.3 Hybrid CNN-Based Feature Extraction

The proposed MediFusionNet model uses a CNN hybrid structure for extracting complementary deep features from multi-modal medical images. After the initial preprocessing stage, the input image goes through the feature extraction process using two different branches: VGG16 and MobileNetV2. This design takes advantage of both the powerful feature learning hierarchical structure of VGG16 and the lightweight design of MobileNetV2, thus allowing the representation of disease-related features within the process.

The VGG16 model is capable of extracting fine spatial and semantic details from convolution layers, while the MobileNetV2 model makes use of depthwise separable convolution and inverted residual blocks in order to extract compact discriminative features at low computational cost. The deep feature vectors from both models are then fused together to create an overall representation that is sent through the feature fusion and classification block. The hybrid feature extraction process is mathematically expressed as

$$F_{\text{Hybrid}} = [F_{\text{VGG16}} \parallel F_{\text{MobileNetV2}}] \quad (2)$$

where F_{VGG16} and $F_{\text{MobileNetV2}}$ denote the feature, vectors extracted from the VGG16 and MobileNetV2 branches, respectively, and $\parallel$ represents the feature concatenation operation used to construct the hybrid feature representation.

3.4 Feature Fusion and Classification

The deep features that are extracted from the VGG16 and MobileNetV2 branches are combined to obtain a unified representation of the input medical image. The MediFusionNet architecture utilizes the approach of feature concatenation so that the model retains the unique features that are learned through the VGG16 and MobileNetV2 models. In other words, the fusion process allows for improved discrimination across different disease categories.

The resulting fused feature vector then goes through fully connected layers with ReLU activations and dropout to minimize the overfitting problem. In the end, the output from a Softmax classifier predicts the probabilities of belonging to each disease class, with the class having the highest probability being chosen as the result. Feature fusion and classification are defined by the equation

$$F_{\text{fusion}} = \text{Concat}(F_{\text{VGG16}}, F_{\text{MobileNetV2}}) \quad (3)$$

where F_{fusion} represents the fused feature, vector obtained by concatenating the deep features extracted from the two parallel CNN branches.

calculation of the final classification probability is done by means of the Softmax function, which is expressed as

$$P(y_i) = \frac{\exp(z_i)}{\sum_{j=1}^C \exp(z_j)}, \quad i = 1, 2, \dots, C \quad (4)$$

where z_i denotes the output score of the i^{th} class, $C = 12$ represents the total number of disease categories, and $P(y_i)$ is the predicted probability for each class. The class having the highest probability is regarded as the final diagnosis of the MediFusionNet framework.

3.5 Federated Learning Framework

In order to maintain secure and private model training, the designed MediFusionNet framework uses FL approach with participation of four hospitals. Each hospital trains its model based on its own dataset of medical images and scans. Patient images and data are not shared by the hospitals; rather, only the model parameters are exchanged with the centralized server.

At each communication round, the central server aggregates the locally trained model parameters using the Federated Averaging (FedAvg) algorithm to construct an updated global model. The updated global model is subsequently redistributed to the four participating hospitals for the next local training iteration. The federated training process is performed for five communication rounds ($E = 5$), as illustrated in Figure 2. After completion of the five rounds, the resulting global model is used for subsequent multi-disease diagnostic inference. The complete federated learning workflow is illustrated in Figure 2.

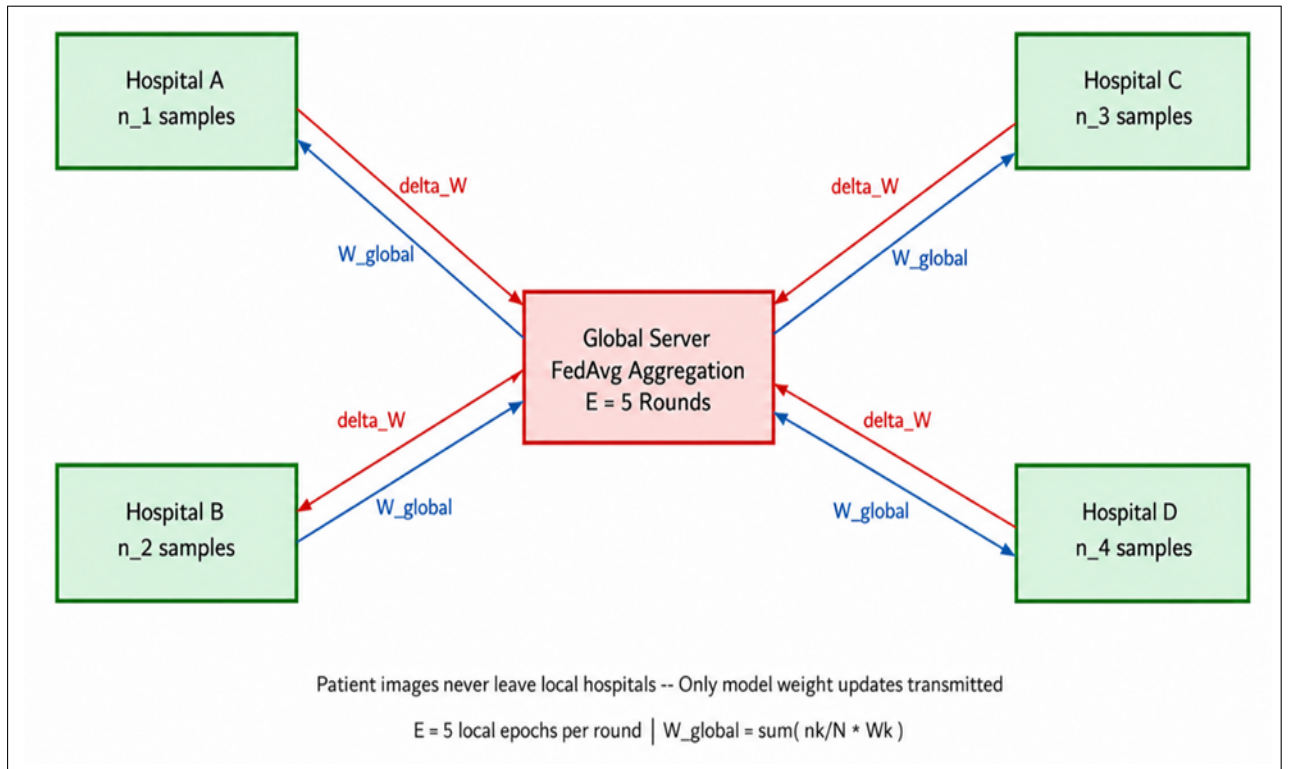


Figure 2. Federated learning architecture of the proposed MediFusionNet.

The global model aggregation is computed as

$$W^{t+1} = \sum_{i=1}^N \frac{n_i}{n} W_i^t \quad (5)$$

where W_i^t denotes the locally trained model parameters of the i^{th} hospital at communication round t , n_i represents the number of training samples at the i^{th} hospital, $n = \sum_{i=1}^N n_i$ is the total number of training samples across all participating hospitals, and W^{t+1} is the aggregated global model distributed for the subsequent training round.

3.6 Web Application

The proposed MediFusionNet architecture is implemented as a web-based application in order to support real-time diagnosis of multiple diseases. The architecture includes a user-friendly interface for uploading images, automatic prediction of diseases, and generation of reports. The entire process of deploying the web application is presented in Figure 3.

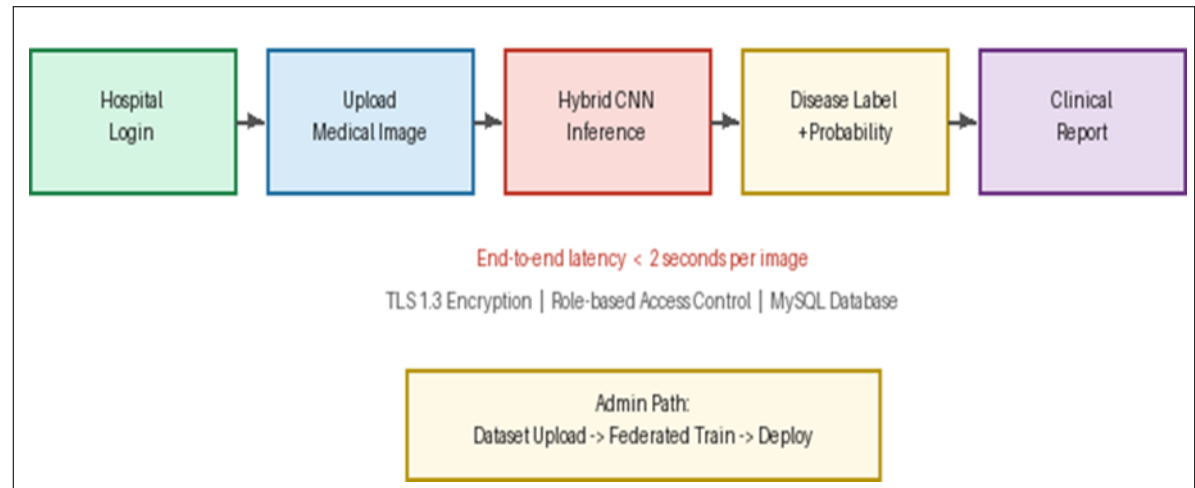


Figure 3. Web-based deployment of the proposed MediFusionNet

The web application is made up of two main components: The Administrator component and the Hospital Clinician component. The administrator handles user authentication, hospital registration, and model deployment, whereas the clinicians will upload the images of will processed for diagnosis purposes. These images will then be processed using the trained MediFusionNet model to produce the predictions and confidence scores, which will automatically produce a clinical report.

3.7 Implementation Environment

The proposed MediFusionNet framework is implemented within a software and hardware environment specifically designed for developing deep learning models, federated learning, and web deployment. This implementation combines the use of deep learning frameworks written in Python with a web framework called Flask to facilitate model training, inference, and clinical diagnosis in real time. The details regarding the hardware, software tools, programming environment, and libraries used in this implementation are shown in Table 2.

Table 2. System configuration and software specifications

Component	Specification
Processor	Intel Core i7 (12th Gen)
GPU	NVIDIA GeForce RTX 4060 (8 GB)
RAM	16 GB DDR4
Storage	512 GB SSD
Operating System	Windows 11 (64-bit)
Programming Language	Python 3.11
Deep Learning Framework	TensorFlow 2.x, Keras
Web Framework	Flask
IDE	Visual Studio Code
Image Processing	OpenCV, NumPy
Data Visualization	Matplotlib, Pandas
Federated Learning	Flower Framework
Model Architecture	VGG16 + MobileNetV2 (Hybrid CNN)

4. Results and Discussion

4.1 Experimental Setup

The proposed MediFusionNet architecture was experimentally analyzed by applying it to four public medical imaging datasets. All the images underwent preprocessing steps such as resizing to 224×224 pixels, normalization, and data augmentation to make sure of the uniform quality of inputs. Then, the datasets were split into training, validation, and testing sets with the share of 70%, 15%, and 15%, respectively.

Implementation of the CNN hybrid model was done via TensorFlow–Keras framework and the model was trained using the Adam optimizer with categorical cross-entropy as the loss function. Performance of the model was evaluated by Accuracy, Precision, Recall, F1 score, and ROC-AUC, which provided a thorough evaluation of the proposed framework. Hardware and software details are given in Table 3.

Table 3. Experimental parameters and configuration

Parameter	Specification
Datasets	Brain MRI, BUSI, Chest X-ray, Lung CT
Input Image Size	224 × 224 pixels
Training: Validation: Testing	70%: 15%: 15%
Loss Function	Categorical Cross-Entropy
Optimizer	Adam
Batch Size	32
Learning Rate	0.001
Activation Function	ReLU, Softmax
Deep Learning Framework	TensorFlow 2.x, Keras
Programming Language	Python 3.11
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, ROC–AUC

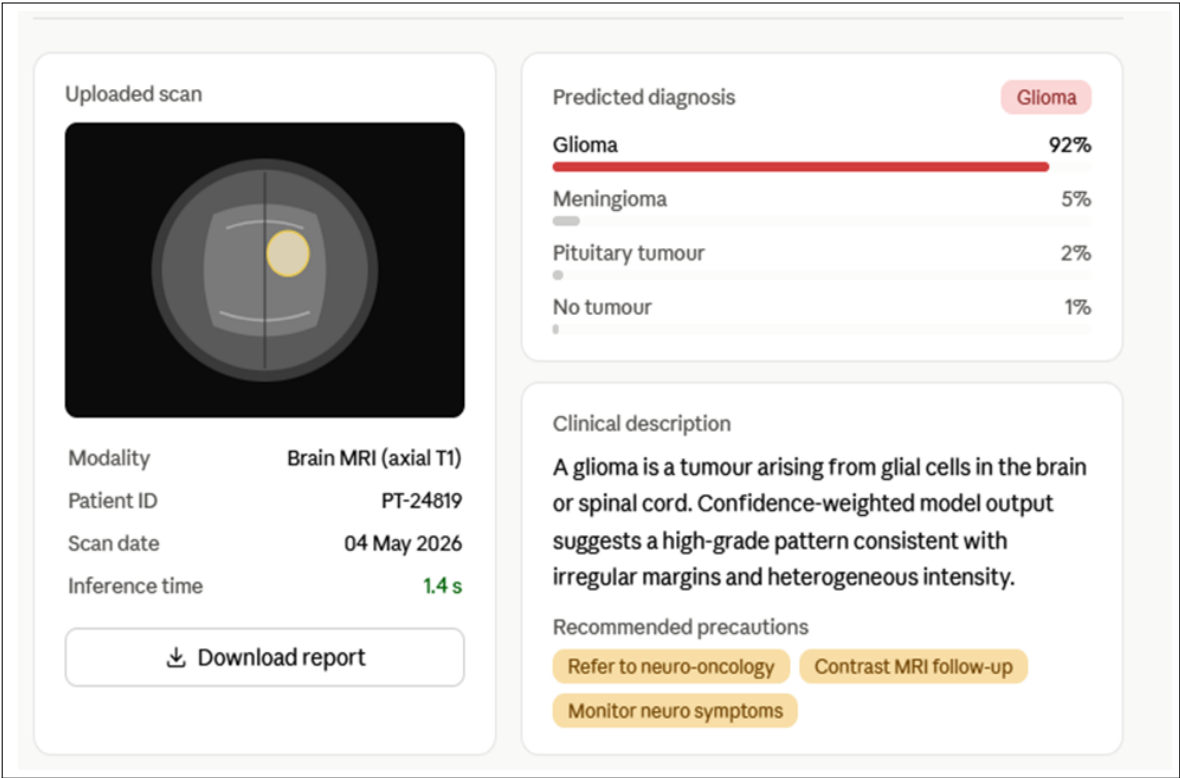


Figure 4. Prediction interface of the proposed MediFusionNet

Figure 4 demonstrates the prediction interface for the MediFusionNet web portal

proposed in this study. The proposed interface can be used by clinicians to upload a medical image and get predictions of the disease class as well as its corresponding confidence score. In addition to the prediction result, other details displayed on the interface include patient details, inference time, a description of the clinical condition, precautions, and a choice to download the clinical report generated.

4.2 Performance Evaluation of the Proposed MediFusionNet

The proposed MediFusionNet framework was tested on four public datasets containing medical images to determine the multi-disease diagnosis ability of the model. The test results were evaluated with the following metrics, where the total results are represented in Table 4. Also, the ROC graphs depicted in Figure 5 show the classification performance of the developed model.

Table 4. Performance comparison across different datasets

Dataset (%)	Accuracy (%)	Precision (%)	Recall (%)	F1-score	ROC-AUC
Brain MRI	93.0	92.4	92.8	92.6	0.968
Breast Ultrasound	91.0	90.6	90.9	90.7	0.951
Chest X-ray	95.0	94.6	94.8	94.7	0.982
Lung CT	92.0	91.5	91.8	91.6	0.962
Average	92.75	92.28	92.58	92.40	0.966

These results from the experiments clearly show that MediFusionNet is able to provide reliable diagnoses on all datasets. High evaluation metrics and ROC-AUC scores reflect its good discrimination and feature learning ability. ROC curves help us to prove its stability and generalization ability in multi-disease classification tasks.

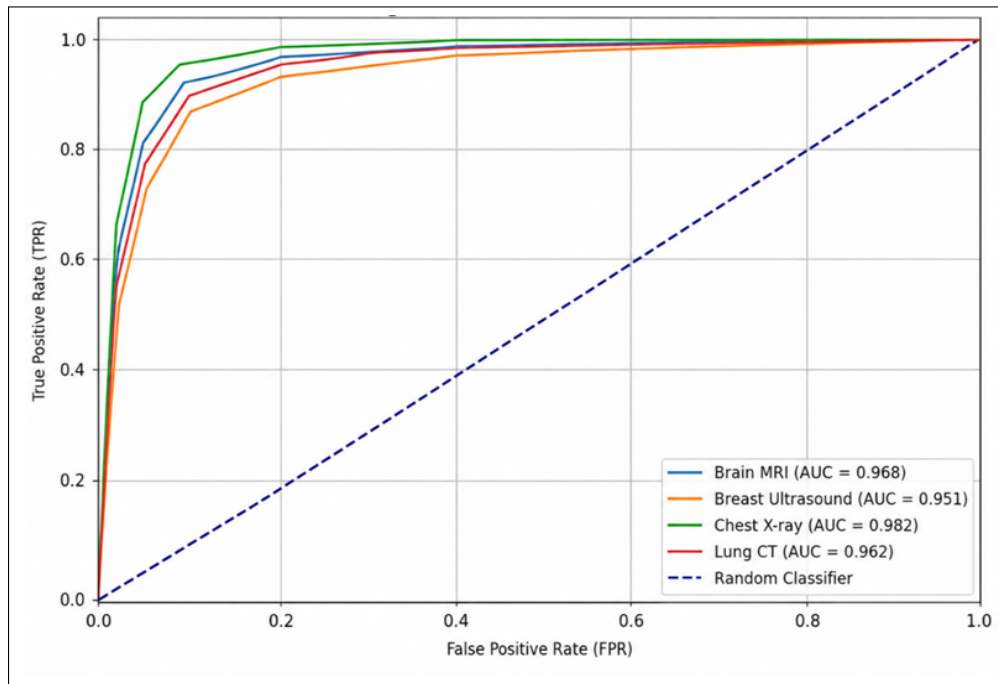


Figure 5. ROC curves of the proposed MediFusionNet

4.3 Discussion

The results obtained from the experiments prove the consistency and reliability of performance provided by the MediFusionNet designed for multi-disease diagnosis through different medical imaging techniques. The use of hybrid feature extraction using CNNs allows the model to extract both low-level and high-level discriminative features that guarantee accurate classification. Also, the federated learning paradigm used allows the collaborative training of the models without compromising the privacy of patient data, which makes the proposed system appropriate for use in distributed settings in the healthcare industry.

5. Conclusion and Future Work

This research introduced MediFusionNet, which is a hybrid CNN-based multi-disease diagnostics web platform used for analyzing Brain MRI, Breast Ultrasound, Chest X-ray, and Lung CT images. The novel framework involves hybrid feature extraction, feature fusion, federated learning, and web-based deployment to provide an efficient, accurate, and secure medical image classification framework. Using various DL models and federated learning to enable collaboration among several users without compromising their privacy, this research

aims to solve the need for computer-aided intelligence diagnosis. The web-based version makes the proposed method even more useful in practice by performing automatic image analysis and generating clinical reports for medical experts. The future research will be dedicated to extending the framework to include new imaging techniques and disease classes, combining multimodal clinical data, making the proposed models more explainable with the use of techniques of explainable artificial intelligence, and evaluating the method on large multi-center clinical datasets.

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