DIAGNOSYS : AN 4-IN-ONE MEDICAL SOLUTION WEBAPP

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***Abstract*—Healthcare for people is one of society's most important issues. To ensure that patients receive the care they require as quickly as possible, it seeks out the best possible and reliable disease diagnosis. Medical system diagnoses are frequently used for rapid disease identification, corrective care, and risk-free treatment of established disorders. Technology is developing even as risks and problems increase. We introduce a fresh paradigm for disease detection in this paper. We will construct a deep learning model that will recover different biomedical data from dispersed and homogeneous sensors.The outcomes will demonstrate the advantages of utilising deep learning technologies in the field of artificial intelligence of medical devices to identify diseases in the process of making healthcare decisions. We will employ several deep learning architectures. One of the most challenging issues in human medicine science is the early detection of chronic disorders. In most cases, patients are not aware of the issue until their symptoms start to appear. One of the popular methods for identifying and determining these conditions and diseases, which aids doctors in making the correct diagnosis, is deep learning.**

[1][2][3][4][5][6] ***Index Terms*—Healthcare, patients,deep learning model, biomedical data, dispersed sensors, homogeneous sensors, advantages, artificial intelligence, medical devices, identify diseases, healthcare decisions, deep learning architectures, human medicine science, early detection, chronic disorders,medical system, rapid disease identification,correct diagnosis.**

I. Introduction and literature review

The rapid advances in deep learning algorithms have had a major impact on various fields, including healthcare. Deep learning algorithms are designed to automatically learn patterns from large amounts of data, making them well suited for applications in medical image analysis and disease diagnosis. In recent years, there has been an increasing interest in using deep learning algorithms for the detection of human diseases.

The usage of deep learning algorithms has had a profound effect on numerous areas, including healthcare. These algorithms, designed to automatically find patterns in large data sets, are ideal for medical image analysis and disease diagnosis. In recent years, there has been growing interest in using deep learning for detecting human diseases. Convolutional Neural Networks (CNNs) are among the earliest and most commonly used deep learning algorithms for disease detection. They extract features from images and classify them into different categories. In medical imaging, they have been used to identify images of healthy and diseased patients or to distinguish between different disease subtypes. Recurrent Neural Networks (RNNs) are another popular deep learning algorithm for disease detection, particularly suited to medical imaging data with temporal dependencies. This research paper will provide a comprehensive overview of the advancements and challenges in using deep learning algorithms for human disease detection, covering various applications in medical imaging, genomics, and electronic health records. Additionally, it will examine the performance of deep learning algorithms in comparison to traditional methods, evaluate their ability to handle medical data complexities and uncertainties and analyze ethical and legal implications in healthcare, such as data privacy, bias and fairness, and accountability. The ultimate goal of this paper is to contribute to the development of reliable, accurate, and transparent deep learning algorithms for disease detection, which has the potential to revolutionize the healthcare system and improve patient outcomes.

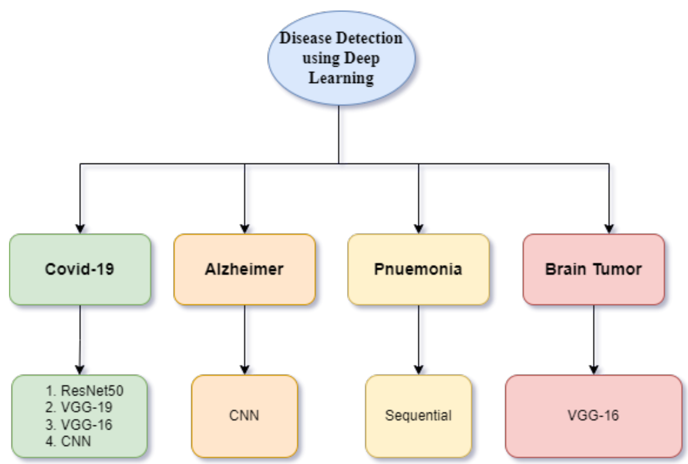

Figure 1 Deep Learning Models

II. Related Works

Medical research has been utilizing deep learning techniques to make early diagnoses of various diseases. One such example is the diagnosis of Parkinson's disease using MRIs and a convolutional neural network (CNN). The CNN was trained to differentiate between healthy brains and those with Parkinson's disease. Another example is the classification of skin lesions into melanoma, basal cell carcinoma, or benign moles using a combination of CNNs and transfer learning. The study was able to improve accuracy in classifying skin lesions. In a similar vein, deep learning models have been used to diagnose Alzheimer's disease using MRI images and a deep neural network (DNN). The model was able to differentiate between healthy individuals and those with Alzheimer's disease. Another area of application is tuberculosis diagnosis from chest X-rays, which was achieved using a CNN trained to classify X-rays into either tuberculosis or normal. A study on melanoma skin cancer also used deep learning algorithms to diagnose the disease using a deep convolutional neural network (DCNN). The DCNN was trained on images of malignant and benign moles and showed high accuracy in diagnosing melanoma. Another research project aimed at the automated detection of tuberculosis from chest X-rays used deep learning algorithms to achieve high accuracy rates. These examples highlight the potential for deep learning in medical diagnosis and the development of effective algorithms for early disease detection. These are a few examples of research and projects related to human disease detection using deep learning algorithms. The field is growing rapidly as deep learning has proven to be an effective tool in diagnosing various diseases with high accuracy.

III. Problem formulation

In this particular research report, we are trying to develop a web application that will detect diseases/segment them into particular disease cases on the basis of CT scan images or X-Ray scans. Further, we are going to implement the model weights and then use flask to make them work on the backend of the project.The models that we are going to use in this will be the most optimized models among(ResNet50, VGG-16 and VGG-19 and one of our own CNN implementation). Then we are going to do a survey analysis of the performance of all these models on our given dataset. Finally, we are going to plot graphs and diagrams to show the end-to-end accuracy on training and validation datasets.

IV. Implementation details

A. Covid-19 Detection:

Coronavirus disease 2019 (COVID-19) is a contagious disease caused by a virus, the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The first known case was identified in Wuhan, China, in December 2019. The disease spread worldwide, leading to the COVID-19 pandemic. COVID-19 transmits when people breathe in air contaminated by droplets and small airborne particles containing the virus. The risk of breathing these in is highest when people are in close proximity, but they can be inhaled over longer distances, particularly indoors.

Here we are detecting whether the patient has Covid-19 or not, using deep learning classification techniques like ResNet50, VGG-16 and VGG-19. Apart from this, we have implemented our own CNN network from scratch. The first 3 models are first pre-trained on the ImageNet dataset and then we used the downloaded weights to carry out a transfer learning on our dataset.We compile the models for all 4 networks and then calculate their accuracy , precision, and recall scores.

1) Dataset:: Covid-19 Chest Xray Images Dataset[7]This dataset contains 125 Covid-19 positive images and 500 Covid-19 negative images. In this dataset there is an imbalance in the number of images of Covid-19 positive to Covid-19 negative, hence we will have to balance it by using data augmentation techniques.

ResNet50 model:
The train data shape is a 224x224x3 pixels matrix. For training the model we have performed 50 epochs with a learning rate of 0.001. The optimizer that we have used over here is Adam Optimizer and the loss function used is binary cross entropy. The test accuracy is 91.94 %, validation accuracy is 96.83 %, and finally, the training accuracy is 97.73%. The precision of the average weighted score is 0.93.

VGG-16 model:
The train data shape is a 224x224x3 pixels matrix. For training the model we have performed 50 epochs with a learning rate of 0.001. The optimizer that we have used over here is Adam Optimizer and the loss function used is binary cross entropy. The test accuracy is 98.39%, validation accuracy is 98.41 %, and finally, the training accuracy is 98.37%. The precision of the average weighted score is 0.98, the recall of the average weighted score is 0.98, and the f1-score of the average weighted score is 0.98.

VGG-19 model:
The train data shape is a 224x224x3 pixels matrix. For training the model we have performed 50 epochs with a learning rate of 0.0001. The optimizer that we have used over here is Adam Optimizer and the loss function used is binary cross entropy. The test accuracy is 95.16%, validation accuracy is 96.83 %, and finally, the training accuracy is 99.78%. The precision of the average weighted score is 0.95, the recall of the average weighted score is 0.95, and the f1-score of the average weighted score is 0.95.

CNN model:
The train data shape is a 150x150x3 pixels matrix. For training the model we have performed 100 epochs with a learning rate of 0.001. The optimizer that we have used over here is Adam Optimizer and the loss function used is binary cross entropy. The test accuracy is 96.77 %, validation accuracy is 96.88 %, and finally, the training accuracy is 94.87%. The precision of the average weighted score is 0.97, the recall of the average weighted score is 0.97 and the f1-score of the average weighted score is 0.97.
The image of the layers visualization is given below:

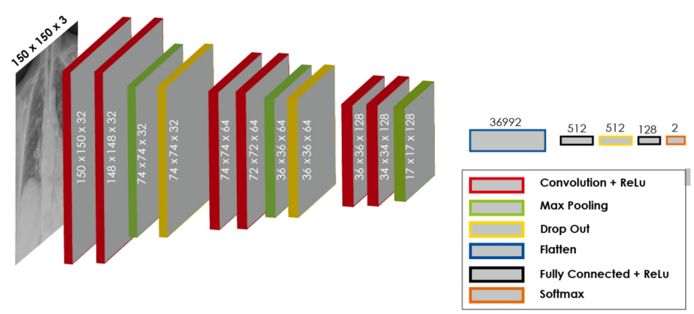

Figure 2 Our Own Architecture

B. Brain Tumor Detection:

A brain tumor occurs when abnormal cells form within the brain. There are two main types of tumors: malignant tumors and benign (non-cancerous) tumors. These can be further classified as primary tumors, which start within the brain, and secondary tumors, which most commonly have spread from tumors located outside the brain, known as brain metastasis tumors Here we are detecting whether the patient has Brain Tumor or not, using a VGG-16 model. Apart from this, we are trying to implement our own CNN network from scratch. The model is first pre-trained on the flower images collected from googleapis.com and then we used the downloaded weights to carry out a transfer learning on our dataset. We compile the models for the above 2 networks and then calculate their accuracy, precision, and recall scores.

1) Dataset:: Brain MRI images Dataset[8]The dataset contains brain MRI images divided into 2 folders directory that is YES or NO. Inside the NO directory, there are 98 images and in the YES directory, there are 155 images.

VGG-16 model:

The train data shape is a 504x450x3 pixels matrix for non-tumor and a 512x512x3 matrix for tumor. For training the model we have performed 30 epochs and a batch size equal to 32. The optimizer that we have used over here is Adam Optimizer and the loss function used is binary cross-entropy. The test accuracy is 89.7% and the training accuracy is 95.79%. The precision of the average weighted score is 0.79, the recall of the average weighted score is 0.65, and the f1-score of the average weighted score if 0.65.

C. Alzheimer Detection:

Alzheimer's disease (AD) is a neurodegenerative disease that usually starts slowly and progressively worsens. It is the cause of 60–70most common early symptom is difficulty in remembering recent events. As the disease advances, symptoms can include problems with language, disorientation (including easily getting lost), mood swings, loss of motivation, self-neglect, and behavioral issues. As a person's condition declines, they often withdraw from family and society In this section, we are going to describe the model that we have trained for classifying Alzheimer's presence in the patient using MRI scans of the brain. We compile the models and then calculate their accuracy, precision, and recall scores.

1) Dataset:: Alzheimer's Dataset (4 class of Images)[**?**]. The data consists of MRI images. The data has four classes of images both in training as well as a testing set they are Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. Inside the training directory, there are 4 subdirectories of Mild Demented(717 images), Moderate Demented(52 images), Non-Demented (2560 images), and Very Mild Demented(1792 images). Inside the testing directory, there are 4 subdirectories of Mild Demented(179 images), Moderate Demented(12 images), Non-Demented (640 images), and Very Mild Demented(448 images).

CNN model::

The train data shape is a 176x176x16 pixels matrix. For training the model we have performed 50 epochs with a batch size of 16. The optimizer that we have used over here is Adam Optimizer and the loss function used is Categorical cross-entropy. The test accuracy is 96.77 %, validation accuracy is 96.88 % and finally, the training accuracy is 94.87%. The precision of the average weighted score is 0.97, the recall of the average weighted score is 0.97, and the f1-score of the average weighted score is 0.97.

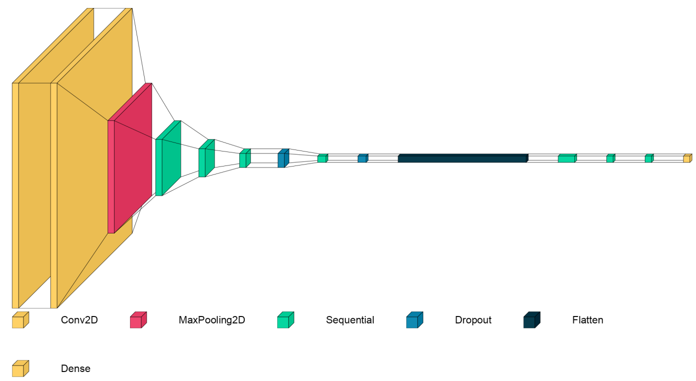

Figure 3 Brain Tumor model accuracies

D. Pneumonia Detection:

Pneumonia is an inflammatory condition of the lung primarily affecting the small air sacs are known as alveoli. Symptoms typically include some combination of productive or dry cough, chest pain, fever, and difficulty breathing. The severity of the condition is variable. Pneumonia is usually caused by infection with viruses or bacteria, and less commonly by other microorganisms. Here we are going to describe the model that we have trained for classifying the pneumonia presence in the patient using an XRay scan of the chest. We compile the models and then calculate their accuracy, precision, and recall scores.

1) Dataset:: Chest X-Ray Images (Pneumonia)[**?**]. The dataset is organized into 3 folders (train, test, value) and contains subfolders for each image category (Pneumonia/Normal). There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal). Inside the training folder, there are 2 sub folders of Pneumonia(3875 Images) and Normal(1341 images). Inside the testing folder, there are 2 sub folders of Pneumonia(390 Images) and Normal(294 images). Inside the validation folder, there are 2 sub folders of Pneumonia(8 Images) and Normal(8 images).

Sequential model::

The train data shape is a 148x148x32 pixels matrix. For training the model, we have performed 20 epochs with a batch size of 16. The optimizer that we have used over here is RMSProp and the loss function used is binary cross entropy. The test accuracy is 86.77 %, validation accuracy is 96.88 %, and finally, the training accuracy is 96.87%. The precision of the average weighted score is 0.97, the recall of the average weighted score is 0.97, and f1-score of the average weighted score is 0.97.

V. UI Layer

A. Services

This section of the web application is where we display all of the working services that are available for the user.

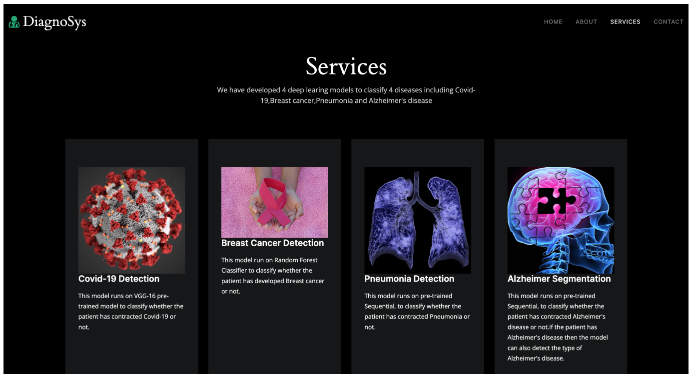

Figure 4 Services UI on the web application

B. Covid 19 Detection

In this section, users can upload an X-ray image of their chest and provide their personal information. The Flask server will receive this information and use a Deep Learning model to classify the image for COVID-19 detection. The classification result will be generated based on the input image and the information provided by the user.

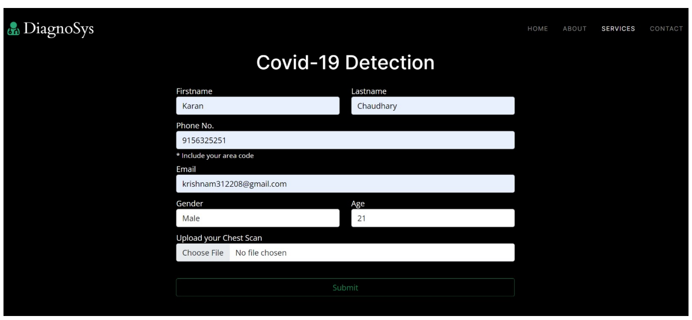

Figure 5 Covid-19 Detection

As a result, we have the consequence generated page which showcases the output denoting whether the patient has contracted Covid-19 or not. The model classifies as POSITIVE(meaning the patient has Covid-19) or NEGATIVE(meaning the patient is healthy). The page also displays the details entered by the user.

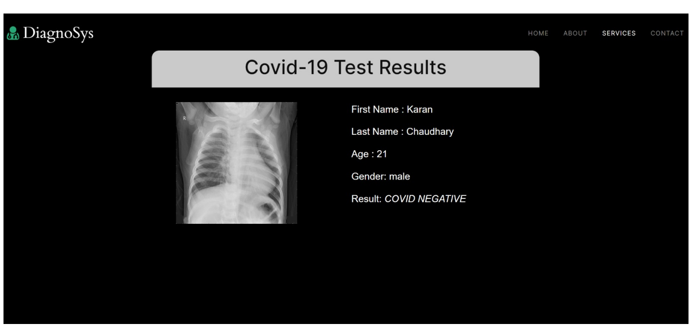

Figure 6 Covid-19 Detection Result

C. Breast cancer Detection

This is the Breast cancer detection section where the user uploads the required details and also fills in their details along with it. The flask server running processes the HTML request and then based on the input sizes generates the classification using the machine Learning model we have used.

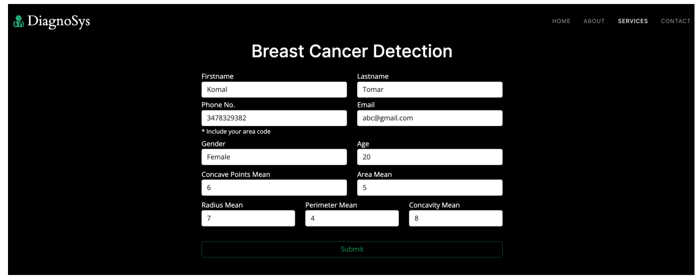

Figure 7 Breast cancer Detection

As a result, we have the result generated page which showcases the output denoting whether the patient has breast cancer or not. The model classifies as cancer Exists(meaning the patient has breast cancer) or does not exist (meaning the patient is healthy). The page also displays the details entered by the user.

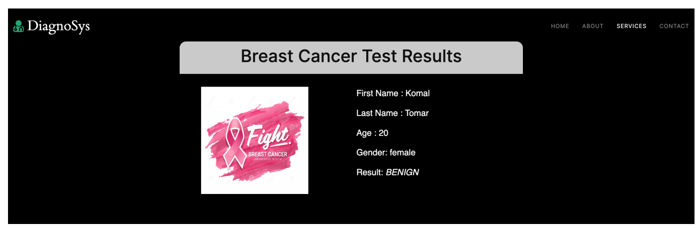

Figure 8 Breast cancer Detection Result

D. Pneumonia Detection

This is the Pneumonia detection section where the user uploads the XRay image of the chest and also fills in their details along with it. The flask server running processes the HTML request and then based on the input image generates the classification using the Deep Learning model we have used.

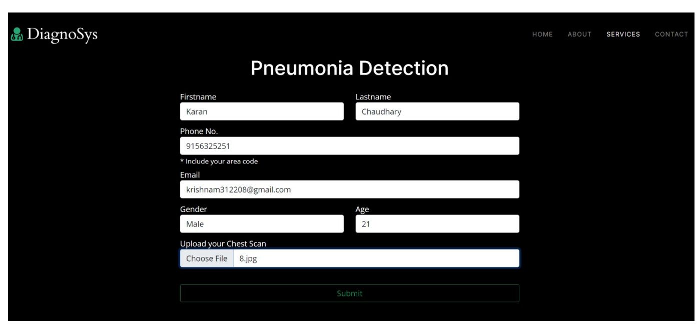

Figure 9 Pneumonia Detection

As a result, we have the result generated page which showcases the output denoting whether the patient has contracted Pneumonia or not. The model classifies as POSITIVE(meaning the patient has Pneumonia) or NEGATIVE(meaning the patient is healthy). The page also displays the details entered by the user.

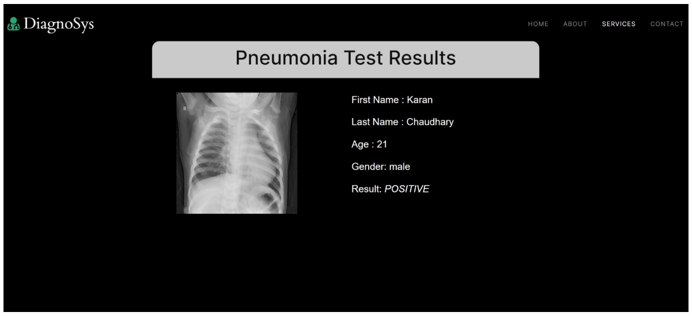

Figure 10 Pneumonia Detection Result

E. Alzheimer Detection

This is the Alzheimer detection section where the user uploads the MRI image of the brain and also fills in their details along with it. The flask server running processes the HTML request and then based on the input image generates the classification using the Deep Learning model we have used.

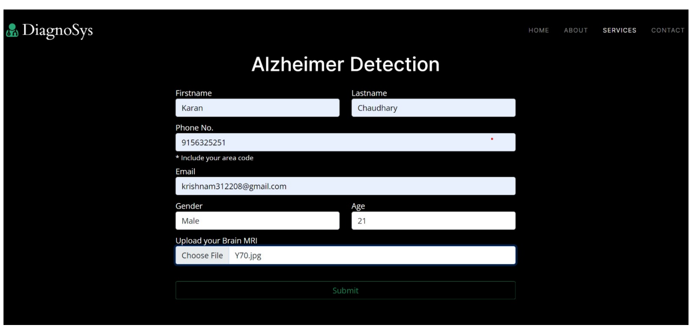

Figure 11 Alzheimer Detection

As a result, we have the result generated page which showcases the output denoting whether the patient has contracted pneumonia. The model classifies whether the patient has Alzheimer then it further classifies the type of Alzheimer's disease and if the patient does not have Alzheimer then it classifies as nonDemented.The page also displays the details entered by the user.

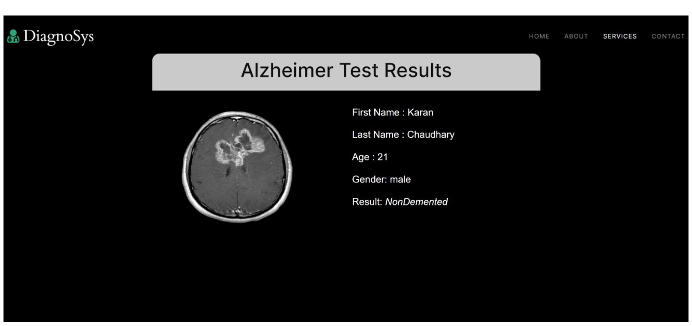

Figure 12 Alzheimer Detection Result

VI. Experimental results

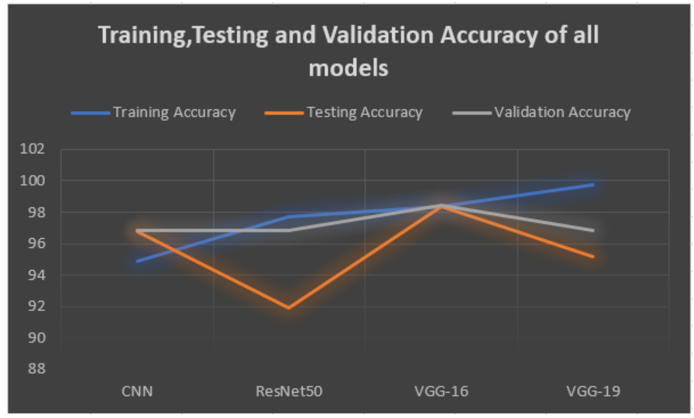

Figure 13 Covid-19 model accuracies

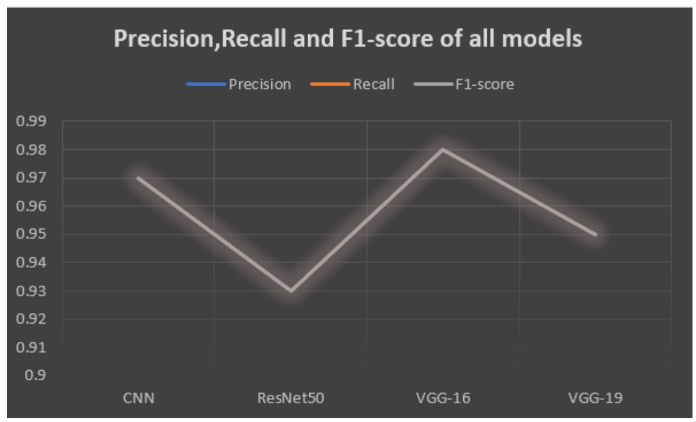

Figure 14 Covid-19 model precision,recall and f1-scores

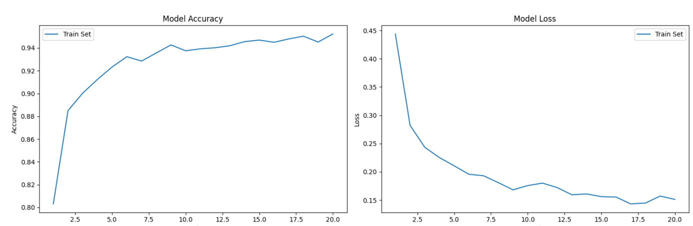

Figure 15 Pneumonia accuracies

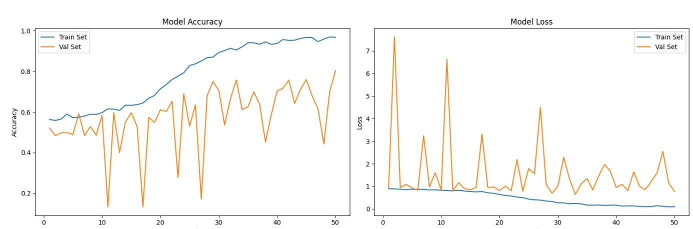

Figure 16 Alzheimer accuracies

Disease	Model Architecture	Accuracy
Covid-19	VGG-16	98.5%
Breast cancer	Random Forest	95.08%
Pneumonia	CNN Sequential	86.77%
Alzheimer	CNN Sequential	96.77%

Figure 17 Table describing the models used.

VII. Conclusion

In conclusion, deep convolutional neural networks (CNNs) have revolutionized the field of image processing and classification, providing remarkable improvements in accuracy and generalization compared to traditional machine learning methods. The ability of CNNs to implicitly learn features through feature detection layers, weight sharing mechanisms, and parallel computations has made them an indispensable tool for image feature representation and classification tasks. The architecture of CNNs closely mimics the structure of the human visual nervous system, further enhancing their effectiveness.

However, despite the tremendous progress, there are still areas that require further exploration and development. One of the key challenges lies in interpretability and explainability. CNNs are often perceived as black box models, lacking transparency in their decision-making process. Future research should focus on developing techniques to provide insights into the internal workings of deep CNNs, such as visualizing and analyzing intermediate representations, attributing importance to specific features, or generating explanations for their predictions. Enhancing the interpretability and explainability of deep CNNs will foster trust, facilitate model validation, and aid in domain-specific applications.

In this paper, we have described our approach in which we are trying to build a DiagnoSys web application. We trained various models and then based on their performance and hyper-parameters narrowed down 1 model for each disease detection. Then we used flask framework from Python to create the integration of the saved weights of the model and the HTML of the website. As a result, we have developed a web application in which doctors or medical professionals can upload images of MRI scans or XRay scans, and the classified report is generated.

VIII. Future Work

Our further approach is to add the download feature to the report that is generated after the classification. We are planning to work more on the models and their accuracy. We also plan to further add a database so that we can manage the user's data and then add more services based on that data.

References

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