ADPT: An Automated Disease Prognosis Tool Towards Classifying Medical Disease Using Hybrid Architecture of Deep Learning Paradigm

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***Abstract*—The Covid 19 beta coronavirus, commonly known as the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), is currently one of the most significant RNA-type viruses in human health. However, more such epidemics occurred beforehand because they were not limited. Much research has recently been carried out on classifying the disease. Still, no automated diagnostic tools have been developed to identify multiple diseases using X-ray, Computed Tomography (CT) scan, or Magnetic Resonance Imaging (MRI) images. In this research, several Tate-of-the-art techniques have been applied to the Chest-Xray, CT scan, and MRI segmented images' datasets and trained them simultaneously. Deep learning models based on VGG16, VGG19, InceptionV3, ResNet50, Capsule Network, DenseNet architecture, Exception and Optimized Convolutional Neural Network (Optimized CNN) were applied to the detecting of Covid-19 contaminated situation, Alzheimer's disease, and Lung infected tissues. Due to efforts taken to reduce model losses and overfitting, the models' performances have improved in terms of accuracy. With the use of image augmentation techniques like flip-up, flip-down, flip-left, flip-right, etc., the size of the training dataset was further increased. In addition, we have proposed a mobile application by integrating a deep learning model to make the diagnosis faster. Eventually, we applied the Image fusion technique to analyze the medical images by extracting meaningful insights from the multimodal imaging modalities.**

***Index Terms*—Disease Prognosis Tool (DPT), CT scan, MRI, Lung Disease, Machine Learning (ML), Deep Learning (DL), Computerized deep learning model, VGG16 model, and Artificial Intelligence in Healthcare**

I. Introduction

Covid-19 will be mostly gone by 2023. Outbreaks require masks despite global vaccination. Most things have returned to pre-Covid-19 levels, and we mourn millions of deaths. Large weddings, stadium concerts, and megachurch services are expected. To meet demand, economies are growing. When Covid-19 suddenly appeared, researchers found a new cluster of pneumonia-like illnesses—testing quickly established that it was a novel influenza virus that had spread from birds to humans or anywhere else. The new virus kills four times as many people as Covid-19. The new virus primarily affects children, like the 1918 pandemic. Just when the vaccine rolled out and people started dreaming of getting rid of the deadly coronavirus, one of the variants of Covid-19, "Delta", appeared in India in late 2021. It was spread excessively to over 179 nations within a brief period by November 2021 [1]. From a national viewpoint, southwest Sydney was the site of 137 (or 34%) of the 403 mortality in Australia related to delta outbreaks [2]. Shortly after the delta variant was released, another variant appeared, and researchers identified it as an omicron.

Even while conventional diagnosis is growing simpler, all these discovered variants and future possible ones still poses a significant risk to medical personnel. Diagnostic test kits are uncommon and expensive. Screening by X-ray and CT is more inexpensive, secure, and accessible. Due to cost and time constraints, traditional X-ray imaging has replaced CT scanning in Covid-19 screening. Even in remote locations, there are an abundance of X-ray scanners [3]. Inadequate awareness of virus-infected areas can result in an error; therefore, radiologists should evaluate X-rays with greater care. This emphasizes the need for quicker and more precise automated diagnosis. Machine learning (ML) and deep learning (DL) are used to diagnose problems in medicine. AI and ML are frequently used to identify Covid-19 in chest CT images and chest radiographs. This is necessary for detecting and screening serious situations. Researchers, physicians, and other healthcare professionals are creating ML or DL-based algorithms for early diagnosis and screening as the epidemic expands. Insufficient research makes it difficult to select a good

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and successful model from the available options.

On the other hand, because deep learning-based techniques are now widely used in medical imaging, it can be challenging to choose an efficient model because each one has a different computational complexity and efficiency level. To modernize our program, we combined cutting-edge computational methodology with advanced technology to diagnose life-threatening diseases. This is the driving force behind the proposed study's goal of creating an automated, low-cost tool for diagnosing diseases that will help doctors or radiologists identify and screen severe illnesses. However, this proposed study has several contributions that can be summarized as follows:

1) Developing a low-cost disease prognosis tool to help radiologists and doctors diagnose Alzheimer's, COVID-19, and lung-infected tissues.
2) Utilizing the existing android technology and making it automated by integrating a deep learning detection model.
3) provide a comprehensive pipeline for researchers using several cutting-edge deep learning methods to understand algorithm patterns and choose their model.

II. Literature Review

While predicting significant diseases using data from multimodal imaging modalities is the primary objective of this research, it is crucial to comprehend the underlying issue and know how researchers have previously resolved similar problems. As a result, the following research articles examine the potential research gaps, driving forces, techniques, and distinctive contributions of each research article.

In [3], the authors classify 400 CT scan images of lung diseases using machine learning. Several machine learning approaches, such as the Multilayer Perceptron (MLP), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) classifier, are utilized to assess and categorize the input image. The output is segmented after the extracted features, and the concentrated model's accuracy is compared. The Gray Level Co-occurrence Matrix (GLCM) is utilized as a result (i.e., to extract attributes). 99.2% accuracy was reported for the KNN model which was the highest. Research on analyzing machine learning algorithms to spot diffuse lung diseases was conducted by researchers [4]. The utilization of 3252 ROIs with 28 attributes should be noted. Principal component analysis (PCA), linear discriminant analysis (LDA), and stepwise selection (forward, backward, and forward-backwards) were used to reduce the number of dimensions. The feature subsets were fed into the machine learning techniques, and the ROIs also used a Deep Convolutional Neural Network.

Reference [5] developed a research model for lung cancer diagnosis using boosted neural networks. The proposed method consists of two steps: ensemble classification and feature selection. Researchers choose the most significant attributes in the first step by using a pre-processing model that combines Newton's Maximum Likelihood with Minimum Redundancy (MLMR) to speed up the classification process. In the second stage, patients are identified using the Boosted Weighted Optimized Neural Network Ensemble Classification method to improve cancer illness diagnosis and lower false-positive rates significantly.

Nine classification algorithms, including one deep learning-based Convolutional neural network (CNN) and five more transfer learning (TL) systems, including VGG16, DenseNet121, DenseNet169, and MobileNet architecture, were used in a research [6]. Although, the highest results came from combining a deep convolutional neural network (DCNN) and a Random Forest (RF) in terms of accuracy and ROC Curve, with 99.41%, 5.12%, 91%, and 99.41%, respectively. A novel structure termed the multi-level cross residual convolutional neural network (ML-xResNet) was introduced to classify lung nodule malignancy [7]. ML-xResNet is developed using three-level parallel ResNets with varying convolution kernel sizes to extract multi-scale properties from inputs. The trial results show that the suggested ML-xResNet, without any additional specific pre-processing, achieves the best results, with a ternary classification accuracy of 85.88% and binary classification accuracy of 92.19%.

Researchers examined the effectiveness of Deep Feed-forward Neural Networks (DFNN) to distinguish between diffuse lung disorders (DLDs) [8]. Six unique radiographic patterns, such as pulmonary consolidation, emphysematous areas, septal thickening, honeycomb, ground-glass opacities, and normal lung tissues, are used to characterize DLDs. With an overall accuracy of 99.60%, nearly 10% higher than the other ML methods, the results show that the DFNN technique has broad applicability. The classification of lung tissue patterns impacted by interstitial lung disease (ILD) in high-resolution computed tomography (HRCT) data was explored and compared using a variety of CNN architectures with and without transfer learning [9]. Various cycle learning rates, hyper-parameter modifications, and data augmentation are investigated for their effects on classification accuracy using the well-known and freely accessible MedGift dataset.

The results of the experiments show that the ResNet18 model based on transfer learning performed better than the baseline on the image dataset considered. To distinguish between cases of Covid-19 pneumonia, cases of non-Covid-19 pneumonia, and healthy controls, the researchers created a deep learning convolutional neural network (CNN) called Deep COVID Detect (DCD) that employed the total chest CT volume [10]. Thirteen international institutions and eight countries' training methods and results are contrasted with AUCs and accuracies above 0.8, including non-China sites in training significantly improved classification performance on the majority of test sites.

III. Research Methodology

The proposed pander's methodology is primarily divided into two parts.: Measurement of Biomedical Imaging (BIOIMG) and Model Deployment Engineering. The BIOIMG is further subdivided into five segments: Medical Data Archive

(MDA), Data Refining Process (DRP), Multi Diseases Classifying Architecture (MDCA), Multi Classification Models (MCM), and Technical Contributions. Besides, the Model Deployment Engineering.

A. MEASUREMENT OF BIOMEDICAL IMAGING (BIOIMG)

1) MEDICAL DATA ARCHIVE (MDA): The three different datasets used in this research were the Covid-19 infected lung tissues (CT scan and X-ray based images), the Alzheimer's dataset (Images of MRI Segmentation) [11], and the lung disease classifier dataset (Chest X-ray data) [12]. Several publicly accessible repositories have been used in the case of Covid-19 lung-infected tissues. We have combined all the datasets to create a dataset of 3200 images, of which 2000 are Covid-19 negative samples, and 1200 are Covid-19 positive samples. Mildly Demented, Moderately Demented, Non-Demented, and Very Mildly Demented are the categories into which the MRI images included in the Alzheimer's dataset [11] are separated. The research dataset's insights are made evident in Table I.

TABLE I: INSIGHTS OF THE RESEARCH DATASETS.

Diseases Type	Total Data Class	Dataset Type	Total Images
Covid-19	2	CT and X-ray	3200
Lung Diseases	15	X-ray	5606
Alzheimer's	4	MRI segmentation	5000

2) DATA REFINING PROCESS (DRP): Prior to using the algorithms, clinical images must be cropped to a precise aspect ratio. Over-fitting can be eliminated, and the suggested models' precision can be increased with augmentation [13]. Image augmentation techniques include comparison, saturation, rotations (45, 135, 225, and 315 degrees), spins, shears, and flips (left-right, up-down, and up-down-left-right). This is how the data has been prepared. This is a very reliable approach because, typically, when working on crucial medical images, the model's accuracy does not increase if the amount of data is insufficient.

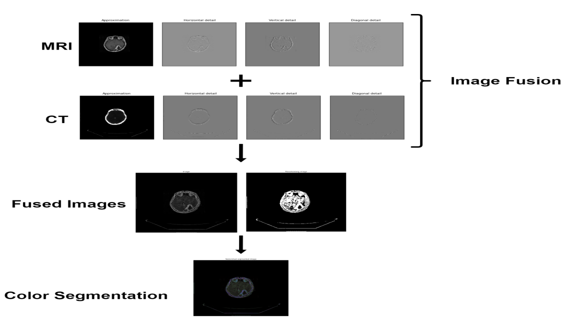

Fig. 1: Data Preprocessing

3) MULTI DISEASES CLASSIFYING ARCHITECTURE (MDCA): This section indicates the Multi Diseases Classifying Architecture (MDCA). The MDCA consists of seven interconnected portions: Data collection, data pre-processing, Classification channels, Model Integration, Performance evaluation, Predictive model, and disease detection software. The MDCA aims to train the machine learning model on top of various diseases-related datasets and predict from the software system. Fig 1 describes the data preprocessing technique used in this experiment where different MRI and CT scan images were taken and their different wavelet transformation (Horizontal, Vertical, and Diagonal) detail were observed. Following that these images were fused and then color segmentation (Watershed) was applied to them.

Overall, by looking at Fig. 2, it can be stated that this research pre-processed their dataset by following a sequential pipeline; for example, applying the image fusion technique and producing a fused image that will be effective while extracting deep features and finding clinical insights are essential to make a decision. When features are selected, it is then forwarded through the classification channels; after that, several state-of-the-art techniques are compared, executed, and evaluated; eventually, the proposed model gives prediction results. Turning to the other side, in the case of Disease Detection AI software, various diseases can be predicted through the software system by putting medical images.

4) DISEASES DETECTION ALGORITHMS (DDA): Pre-trained models for classifying medical images have many benefits, especially when dealing with complex image data. Over the past few years, starting with the well-known AlexNet in 2012, more sophisticated architectures such as VGG-19, ResNet50, Xception, and DenseNet121 have served some of the highest-performing techniques. The Keras library offers these models, valuable functions and pre-trained weights. VGG19, VGG16, InceptionV3, ResNet, EfficientNET, Xception, DenseNet architecture, CapsuleNetwork, and Customized Convolutional Neural Network are just a few of the pre-trained models used in this study (Custom CNN). But because better accuracy was observed on top of these cutting-edge models, this section only covers the VGG19, VGG16, InceptionV3, and DenseNet models. The VGG machine learning model variants that emphasize the CNN's depth feature are VGG16 and VGG19. The input, hidden, convolutional, and fully connected layers make up this model.

Moreover, the CNN-based InceptionV3 model's underlying architecture. Label smoothing is one of the features this version improves. The customized CNN model was finally proposed to identify lung diseases from chest X-ray images. This model has been re-implemented with hyper-parameter optimization and compared to the abovementioned models.

5) TECHNICAL CONTRIBUTIONS: This study makes several technical advances. First, fused images have been created using the image fusion technique, making clinical image analysis and feature extraction much more straightforward for all radiologists and medical professionals. Second, to enhance our training image sample and reduce model overfitting difficulties, data augmentation techniques such as rotations (45, 135, 225, and 315), spins, shears, and flips (Flip left-right, Flip up-down, and Flip up-down-left-right) are utilized. Thirdly, several pre-trained models are run, evaluated against other cutting-edge techniques, and tuned appropriately by modifying parameters. In order to train a customized version of

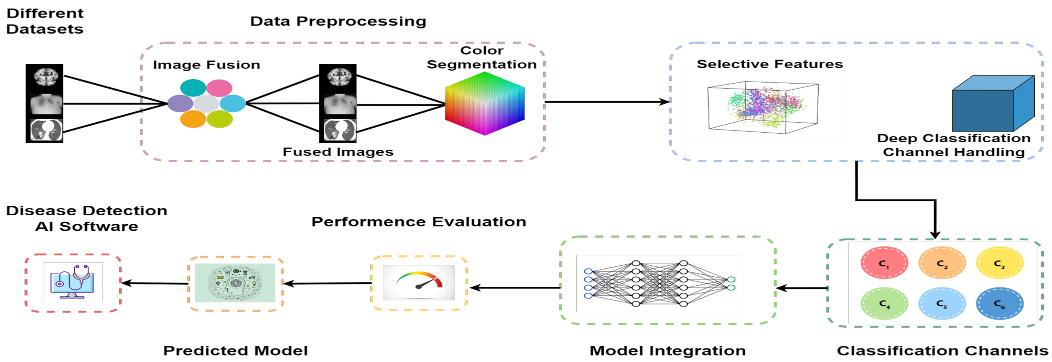

Fig. 2: Architecture design of the multi diseases classifying architecture (MDCA). Various datasets have been utilized and processed before applying the machine learning model by following the seven steps demonstrated in the MDCA.

a Traditional Convolutional Neural Network (TCNN), medical data sets were utilized.

In addition, we have contributed to a dedicated Machine Learning library for medical imagining, proposed an adaptable specialized approach to make a dynamic Artificial Intelligence (AI) software integration, and provided medical decision-making support system tools for the medical individual.

6) MODEL TRAINING AND TESTING: All models are run on an Intel Core i9-10885H (8 Core, 16MB Cache, 2.40 GHz to 5.30 GHz, 45W, vPro), 32GB RAM, and an NVIDIA Quadro RTX 5000 with 16GB GDDR6. Using the train and test datasets, we trained and tested our models. The loss function was categorical cross-entropy loss with the Adam optimizer. The target and batch sizes of the image were 224x224 and 32, respectively. Finally, each model's epoch size was set to 50-100.

B. MODEL DEPLOYMENT ENGINEERING

After creating a machine learning model, it is critical to deploy it into a web server to develop automated clinical tools that can assist doctors or radiologists. The Flask web server was chosen as a Lightweight Web Server Gateway Interface (WSGI) web application framework [14]. Because this is a communication protocol, creating a Representational State Transfer Application Program Interface (REST API) is necessary when deploying the machine learning model into the WSGI. Data will be transmitted through this REST API. Fig. 3 depicts the required production stage after the model has been validated.

At this phase, we have designed three types of API for accessing through an android and web application. For example, Covid-19 detection API (X-ray and CT based), lung diseases detection API (X-ray based), and Alzheimer's disease prognosis API (MRI image segmentation). It is to be mentioned that all of these APIs are designed through Flask micro web framework, and we are extending the platform taking favour of the Django REST framework.

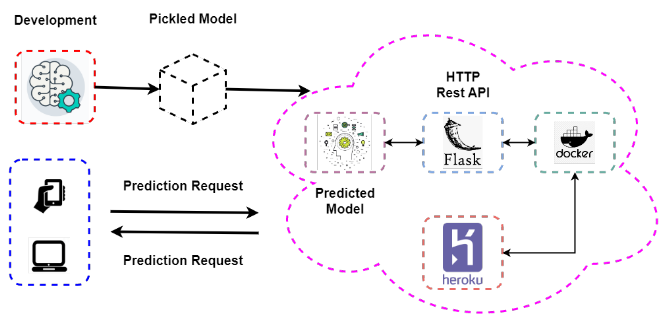

Fig. 3: Representing a comprehensive pipeline for deploying a clinical machine learning model into the web server for accessing a software system, e.g., android application and web application.

IV. THE OUTCOME OF THE EXAMINATION

The Outcome of the Examination is classified into three parts: Classification Metrics Quantifying (CMQ), Evaluating the MDCA and Observation & Discussions. The experimental results of this proposed study have subsequently been described in the following subsections.

A. CLASSIFICATION METRICS QUANTIFYING (CMQ)

The Classification Metrics Quantifying (CMQ) section illustrates the model's empirical consequences through various state-of-the-art techniques. While this research indicates identifying multiple diseases from the imaging modalities, three different datasets are considered, e.g., Chest X-ray images (lung diseases), CT scan (Covid-19) and MRI (Alzheimer's), for measuring the model's prediction ability. It is to be mentioned that a satisfactory accuracy (96%) was obtained among the six state-of-the-art algorithms for detecting Alzheimer's (MRI-based images) through the VGG16 model. On the other hand, the Exception and DenseNet models excellently predicted Alzheimer's alongside the VGG16 and can be considered benchmark models based on their satisfactory execution.

In classifying and predicting Covid-19 diseases on X-ray imaging modalities, the VGG19 model was discovered to have a 98% forecasting credibility. Apart from this, the InceptionV3 network can accurately distinguish the Covid-19 disease from CT scan-based images with a performance score of 96%. Eventually, various pre-trained models were applied at the

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beginning stage for detecting lung disease on X-ray-based images, e.g., Capsule network, VGG16, VGG19, InceptionV3, ResNet50, Exception Optimized CNN, and Vanilla CNN. Through an extensive investigation, it can be stated that 96% accuracy was achieved on the Capsule network with complete datasets. Still, only an 80% performance score was observed on the optimized CNN model combined with a sample dataset.

The Precision (P), Recall (R), F1-Score (F1), and Accuracy in detecting different medical diseases from multimodal imaging modalities, such as CT, X-ray, and MRI segmentation, are displayed in Table II, III, IV, and V. Here, precision demonstrates how numerous of the precisely anticipated circumstances transpired favourably. Recall shows how many actual positive situations can be accurately predicted. The F-score, also called the F1-score, measures the model's performance accuracy in a specific dataset.

TABLE II: CLASSIFICATION REPORTS OF ALZHEIMER'S DISEASES DETECTION ON MRI SEGMENTATION IMAGES

Algorithm	For the case of "0."				For the case of "1."			
	Image Type	P	R	F1	P	R	F1	Accuracy Score
Exception	MRI	0.94	0.95	0.95	0.95	0.94	0.94	0.94
VGG16	MRI	0.94	0.98	0.96	0.98	0.94	0.96	0.96
VGG19	MRI	0.85	0.98	0.91	0.98	0.83	0.90	0.91
ResNet50	MRI	0.78	0.89	0.83	0.87	0.75	0.81	0.82
DenseNet	MRI	0.94	0.95	0.95	0.95	0.94	0.94	0.94
InceptionV3	MRI	0.92	0.82	0.87	0.84	0.93	0.88	0.88

TABLE III: CLASSIFICATION REPORTS OF COVID-19 DISEASE DETECTION ON X-RAY BASED IMAGING MODALITIES.

Algorithm	For the case of "0."				For the case of "1."			
	Image Type	P	R	F1	P	R	F1	Accuracy
InceptionV3	Chest X ray	0.92	0.97	0.94	0.83	0.60	0.70	0.91
RESNET	Chest X ray	0.80	0.92	0.86	0.88	0.73	0.80	0.83
VGG19	Chest X ray	0.95	0.99	0.97	0.99	0.94	0.96	0.97
Xception	Chest X ray	0.96	0.86	0.91	0.89	0.97	0.93	0.92
CNN	Chest X ray	0.52	0.81	0.63	0.33	0.11	0.16	0.49
ModifiedCNN	Chest X ray	0.77	0.33	0.46	0.62	0.92	0.74	0.65

TABLE IV: CLASSIFICATION REPORTS OF COVID-19 DETECTION ON TOP OF CT SCAN-BASED IMAGES.

Algorithm	For the case of "0."				For the case of "1."			
	Image Type	P	R	F1	P	R	F1	Accuracy Score
InceptionV3	CT-scan	0.92	0.99	0.96	0.99	0.93	0.96	0.96
RESNET	CT-scan	0.66	0.91	0.77	0.89	0.59	0.71	0.74
VGG19	CT-scan	0.75	0.77	0.76	0.79	0.78	0.78	0.77
Xception	CT-scan	0.72	0.94	0.81	0.93	0.68	0.78	0.80
CNN	CT-scan	0.53	0.46	0.49	0.55	0.62	0.58	0.54
ModifiedCNN	CT-scan	0.67	0.46	0.54	0.60	0.78	0.68	0.62

TABLE V: CLASSIFICATION REPORTS OF LUNG DISEASE DETECTION ON X-RAY BASED IMAGES.

Algorithm	For the case of "0."				For the case of "1."			
	Image Type	P	R	F1	P	R	F1	Accuracy
Capsule Network	X ray [Full Dataset]	0.92	0.99	0.96	0.99	0.93	0.96	0.96
Capsule Network	X ray [Sample Dataset]	0.66	0.91	0.77	0.89	0.59	0.71	0.74
Optimized CNN	X ray [Full Dataset]	0.75	0.77	0.76	0.79	0.78	0.78	0.77
Optimized CNN	X ray [Sample Dataset]	0.72	0.94	0.81	0.93	0.68	0.78	0.80
Vanilla CNN	X ray [Full Dataset]	0.53	0.46	0.49	0.55	0.62	0.58	0.54
Vanilla CNN	X ray [Sample Dataset]	0.67	0.46	0.54	0.60	0.78	0.68	0.62
Exception	X ray [Full Dataset]	0.67	0.61	0.69	0.44	0.55	0.56	0.65
Exception	X ray [Sample Dataset]	0.41	0.65	0.50	0.12	0.05	0.07	0.35
VGG16	X ray [Full Dataset]	0.52	0.75	0.64	0.60	0.56	0.62	0.57
VGG16	X ray [Sample Dataset]	0.42	0.73	0.54	0.40	0.35	0.40	0.37
VGG19	X ray [Full Dataset]	0.75	0.77	0.78	0.82	0.78	0.76	0.79
VGG19	X ray [Sample Dataset]	0.51	0.68	0.72	0.78	0.61	0.60	0.68
ResNet50	X ray [Full Dataset]	0.67	0.89	0.79	0.54	0.51	0.57	0.62
ResNet50	X ray [Sample Dataset]	0.47	0.79	0.59	0.34	0.31	0.27	0.45
InceptionV3	X ray [Full Dataset]	0.72	0.75	0.67	0.88	0.78	0.79	0.73
InceptionV3	X ray [Sample Dataset]	0.67	0.72	0.66	0.85	0.73	0.78	0.68

B. EVALUATING THE MDCA

These well accepted performance measures are employed in this study instead of examining the model's accuracy, which may not be beneficial. Inadequate model assessment could lead to overfitting problems. As the resulting dataset contains the binary category, the 2 x 2 matrix of 4 values for the binary classification according to the Covid-19 classification is shown in Fig. 4a and Fig. 4b.

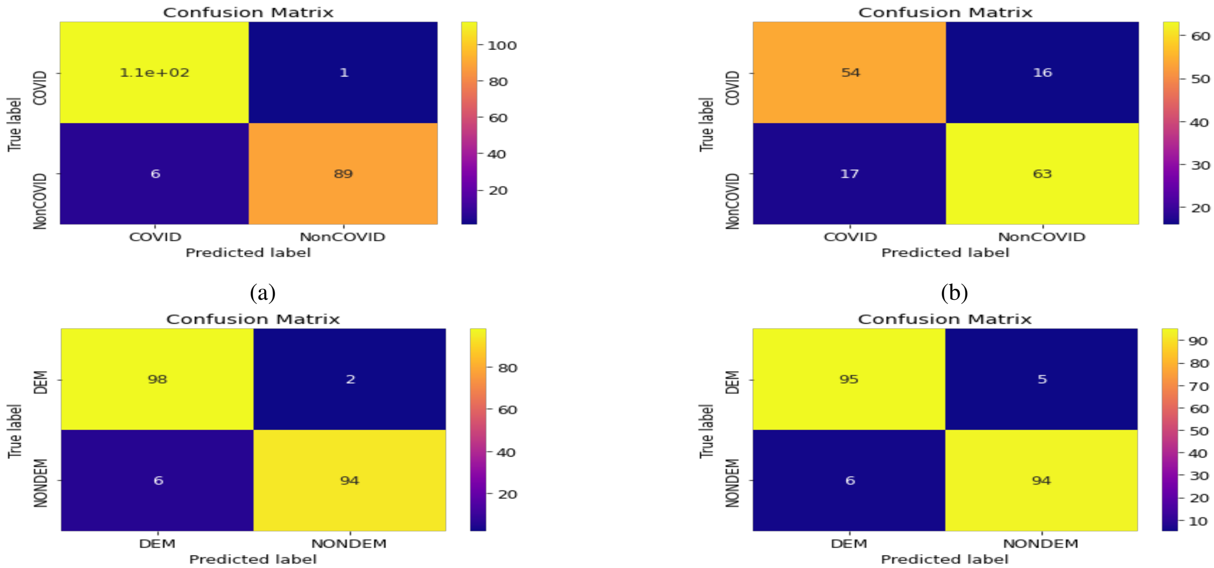
The confusion matrix for classifying Alzheimer's diseases is shown in Fig. 4c and Fig. 4d. The Confusion matrix and its anticipated values are shown in the aforementioned Fig. 4a, 4b, 4c, and 4d. The output of a classification algorithm can be summarized using a confusion matrix [15]. Examples of the four different values that are generally included in it are True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) [16]. Types 1 and 2 of the Confusion Matrix are False Positive (FP), and False Negative (FN) mistakes. Because the actual value for Type-1 was negative while the model predicted a positive value, the expected value was mispredicted.

On the other hand, the prospective value for Type-2 was incorrectly predicted, with the model predicting a negative value when the actual value was positive [17]. As an illustration, the Confusion Matrix of DenseNet and VGG16 model is described below in summary form in terms of classifying Alzheimer's on MRI image segmentation, demonstrating how accurately the model predicted.

C. OBSERVATION & DISCUSSIONS

This particular research article has addressed the issues regarding models' loss-function and overfitting with satisfactory accuracy. Additionally, in order to choose the most effective technique for identifying Covid-19-infected tissue from CT-scan and X-ray data, this work also addresses hyperparameter tweaking and subsequent comparisons.

This research observed that the researchers conducted research adequately to identify Covid-19 diseases. Still, it is to be mentioned that several variants of Covid-19 will appear in the future, so a multi diseases prediction system must be designed at this moment since we are in a global pandemic moment. However, this research integrated various medical disease datasets apart from the Covid-19 image dataset to take the proposed model to a satisfactory level. Finally, we have presented a software system that would be a benchmark for the case of physicians because medical diseases can be analyzed effectively through the proposed system, which would lower human resources and other clinical costs. This cost-effective prognosis model will assist every radiologist and doctor in



(a) (b) (c) (d)

Fig. 4: The Confusion matrix for (a) VGG-19 on X-ray images (b) InceptionV3 on CT scan images (c) VGG16 on MRI images (d) DenseNet on MRI images segmentation.

making a significant decision by analyzing the medical image, e.g., X-ray, CT scans, and MRI segmentation.

V. Conclusion

The Covid-19 epidemic has caused a shocking number of fatalities and damages worldwide. Most people are still ignorant of the disease dynamics and risk factors as the pandemic spreads worldwide. The healthcare industry's personnel and modern technology shortage is the primary cause of rising mortality rates. Analyzing risk factors becomes increasingly challenging without the proper tools. This study will use X-ray, CT, or MRI images to help patients and medical professionals identify diseases. Additionally, by assisting with remote triaging of Covid-19 patients, the proposed application can lessen hospital workload and contamination risk. Future iterations of this research will employ a variety of datasets to analyze and identify severe diseases correctly. When creating a deep learning model, it is essential to consider a sizeable number of Covid-19 X-ray images. The deep-learning model with VGG-16 performs better than all others in predicting from X-ray images.

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