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DETECTION OF MULTIPLE DISEASES FROM CHEST X-RAY IMAGES USING VARIOUS DEEP LEARNING APPROACHES

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Abstract

A vital field of study is multiple illness detection, which attempts to enhance healthcare outcomes by simultaneously recognizing many diseases in individuals. A single illness is identified at a time in the conventional method of disease identification, which is time-consuming, expensive, and usually leads to missed diagnoses. Because of developments in machine learning and artificial intelligence, many illness detection models have been created that can aid in the accurate and speedy diagnosis of multiple diseases. These models use information from a variety of sources, including medical records, lab test results, and imaging data, to discover trends and forecast the risk of certain illnesses. Pneumonia, COVID19, and tuberculosis are just a few of the diseases and disorders that are analyzed, classified, and predicted using the many models that are put forward in this study and research. The public dataset utilized for illness categorization and prediction comprises 7135 chest X-ray images that have been divided into four categories: normal, COVID19, pneumonia, and tuberculosis. Since the dataset being utilized is imbalanced, we gave Class weights to it in order to reduce overfitting while training deep learning models. Several Machine Learning and Deep Transfer Learning Models, including Convolutional Neural Network, Inception-V3, EfficientNetB0, Resnet, and VGG-16, have been deployed for the prediction and classification of multiple diseases. The accuracy of the CNN deep learning model is 82%, the accuracy of Inception-V3 is 86%, EfficientNetB0 is 91%, and Resnet15V2 is 92%. On top of that, the VGG-16 deep learning model outperformed competing models to reach accuracy of 95.3%, with precision, recall, and F1-Score at 96%, 97%, and 98%, respectively.

Keywords: Machine Learning; Deep Learning; Artificial Intelligence; Pneumonia; COVID19; Tuberculosis; Chest X-Rays (CXR); Convolutional Neural Network (CNN); EfficientNetB0; InceptionV3; Resnet; VGG16;

I. INTRODUCTION

There has been a sharp increase in interest and excitement recently for the study of and development of technologies that can help in the early diagnosis and prognosis of several numerous illnesses. Early recognition of disease is essential for prompt and efficient treatment, which can significantly enhance patient outcomes. The process of finding and diagnosing many diseases using diverse diagnostic instruments and methodologies is known as Prediction and Classification of Multi-disease Detection Using Deep Transfer Learning Approaches. When a patient displays symptoms that might be suggestive of many diseases, forecasting and classification of multiple diseases become extremely important. When a patient has many co-existing diseases, traditional diagnostic techniques often focus on one disease at a time, which can delay diagnosis and treatment. Using a multi-disease strategy allows healthcare professionals to screen for and diagnose communicable diseases simultaneously, which can speed up the diagnosis process and enhance patient care.

Algorithms for multi-disease identification and prediction are relatively newcomers to the healthcare technology scene. The need to use healthcare data to improve patient outcomes and treatment led to the development of these models. Healthcare data generation is increasing every day. Artificial intelligence (AI) and machine learning are being used more and more in the healthcare industry. These technologies have made it feasible to create multi-disease prediction and detection models by employing algorithms to analyze enormous volumes of data and uncover patterns that may be utilized to anticipate and diagnose illnesses. One of the earliest applications of a multi-disease prediction model is the Framingham Heart Study, which was launched in 1948 and is still going strong today [1].

The study gathered data on the health of thousands of individuals over the course of several decades, utilizing this data to develop a cardiovascular disease prediction model. Recent advances in research have led to the development of multi-disease prediction models for a number of ailments, such as cancer, diabetes, and infectious diseases. These models usually make use of machine learning algorithms that may examine a range of patient data, such as medical records, imaging investigations, and test results. In addition to prediction models, researchers have developed detection algorithms that can identify illnesses at an early stage. For instance, researchers have developed models that can analyze mammograms and other medical images to look for early signs of breast cancer. The development of multi-disease prediction and detection algorithms is a significant advancement in healthcare technology that has the potential to improve patient outcomes and reduce healthcare costs. But as new technologies develop, it is vital for researchers and decision-makers to carefully assess these difficulties since these models also raise serious ethical and privacy issues.

Among other technical advancements, artificial intelligence and machine learning algorithms have considerably increased the accuracy and effectiveness of multiple illness detection. These technologies are capable of swiftly analyzing vast volumes of patient data, such as prior medical histories, test results, and imaging studies, in order to find trends and deliver accurate diagnoses. The ability to identify several illnesses with a single diagnostic test or instrument is a hopeful advancement in medicine that has the potential to significantly improve patient outcomes while also lowering healthcare expenditures. This article suggests a diagnostic system for predicting and categorizing a variety of illnesses, such as COVID-19, tuberculosis, and pneumonia, utilizing various artificial intelligence and deep learning models and methodologies.

Pneumonia:

Infections frequently result in pneumonia, an inflammation of the lungs. A few of the germs that could be responsible for the illness are bacteria, viruses, and fungi. Symptoms of pneumonia include coughing, fever, chills, chest discomfort, shortness of breath, and tiredness and can range from mild to severe. Pneumonia is a common illness that can affect people of all ages. WHO estimates that 740,180 children died from pneumonia in 2019, which represents 14% of all fatalities among children under the age of five. Pneumonia can be brought on by bacteria, fungi, viruses, and other organisms. Pneumonia may be avoided by getting vaccinated, eating a healthy diet, and taking care of environmental problems. Only one-third of children who acquire pneumonia receive the necessary treatments, notwithstanding the fact that pharmaceuticals can cure pneumonia caused by bacteria [4].

"National, regional, and state-level pneumonia and severe pneumonia morbidity in children in India: modelled estimates for 2000 and 2015" was the title of a research by Brian Wahl et al. [2] The results of their study show the following. A 41% decline in pneumonia cases was estimated to have occurred in Indian children under the age of five who were HIV-uninfected, going from an estimated 838 million cases to 498 million cases. In India, there were 657 cases of pneumonia per 1000 children under the age of five in 2000, and 403 cases per 1000 children under the age of five in 2015. In 2015, India saw an estimated 0.38% national case fatality rate for pneumonia. According to estimates, there were 8 million cases of severe pneumonia in 2015, with an incidence rate of 68 cases per 1000 children and a case fatality rate of 22.6 percent. The three states with the highest estimated numbers of pediatric pneumonia cases in 2015 were Uttar Pradesh (12.4 million), Bihar (7.3 million), and Madhya Pradesh (4.6 million). Kerala saw an 82% decrease in pneumonia incidence between 2000 and 2015, which was the largest decrease. In two states, Uttar Pradesh (565 cases per 1000 children) and Madhya Pradesh (563 cases per 1000 children), the incidence of pneumonia was more than 500 cases per 1000 children in 2015.

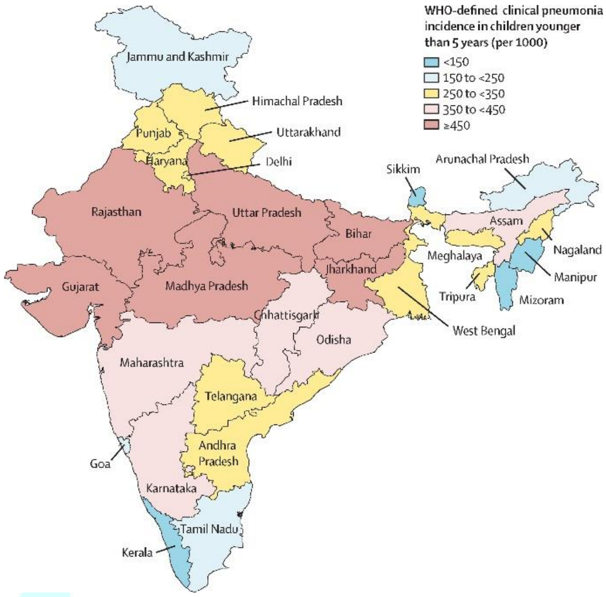

Figure 1. Incidence of clinical pneumonia as defined by the WHO in India by state in 2015 [2]

Tuberculosis:

The World Health Organization [3], reckons that 1.6 million people died from TB in 2021, including 187 000 people living with HIV. Following HIV and AIDS as the third leading causes of mortality globally, 10.6 million cases of tuberculosis (TB) were reported globally in 2021, including 3,400,000 women, 1,2,000,000 children, and 6,400,000 males. TB is the second most lethal infectious disease in the world after COVID-19. People of all ages and from all nations are impacted by TB. But TB can be prevented and treated. Multidrug-resistant tuberculosis, or MDR-TB, continues to be a public health issue and a security risk. In 2021, just one in three individuals with drug-resistant TB received treatment. It is anticipated that TB diagnosis and treatment would prevent 74 million deaths between 2000 and 2021. For TB prevention, diagnosis, treatment, and care, US$ 13 billion is needed yearly in order to attain the global objective established at the 2018 UN high level summit on TB. United Nations' SDGs, the department of Sustainable Development Goals aims to totally eradicate Tuberculosis (TB) by 2023.

Varshney et al. [5], represented a study in which they explained that the overall number of TB deaths fell by 15.4% in 2020 compared to 2019, with decreases seen in 28 of India's 36 states during this time. Despite an increase in overall fatalities in 2021 compared to 2020, there were declines in 2021 compared to 2019. In India, the number of TB deaths among people with HIV fell by 16.0%. Though not consistent between states, there was a noticeable increase in TB fatalities among indigenous groups on a nationwide basis.

Table 1. Trends in TB Reporting in 2019, 2020 and 2021 [5]

Year	Total TB cases detected	% change in total TB cases	Total pulmonary TB cases detected	% change in TB pulmonary cases	Total extra-pulmonary TB cases detected	% change in TB extra-pulmonary cases
2019	2,404,815	Reference	1,764,416	Reference	640,399	Reference
2020	1,850,670	-24.9	1,291,986	-26.8	513,684	-19.8
2021	2,135,670	-11.2	1,528,000	-13.4	607,830	-5.1

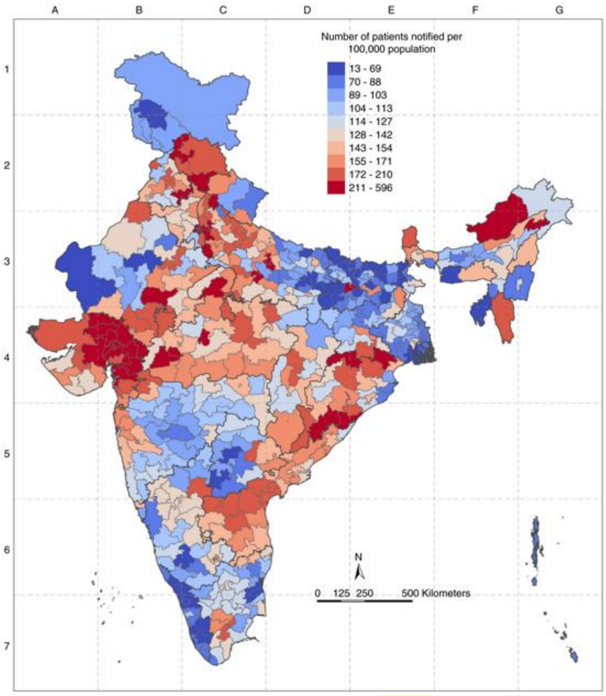

Figure 2. Breakdown of Overall TB Reporting rate deciles per 100,000 people per region [6]

COVID19:
The SARS-CoV-2 virus, in accordance with WHO [7], is the root cause of the inflammatory disorder known as coronavirus disease (COVID-19). The majority of those infected with the virus will develop a mild to severe respiratory disease, but most will recover without the need for special treatment. Some people, however, will develop serious illnesses that call for medical care. The likelihood of developing a major illness is higher among the elderly and in those with underlying medical diseases including cancer, diabetes, cardiovascular disease, or chronic respiratory issues. Anyone, regardless of age, could become gravely ill or pass away with COVID-19.

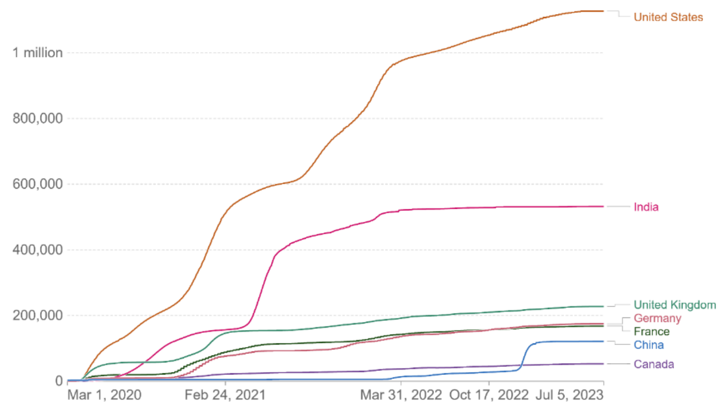

Figure 3. Cumulative Confirmed COVID-19 Deaths [8]

Machine Learning:
Creating models and algorithms that can learn from data and make predictions or judgments without being explicitly programmed is the goal, the area of artificial intelligence known as machine learning. With the use of machine learning, computers will be able to automatically improve their performance at a given task.
The fundamental components of machine learning consist of three things: data, models, and algorithms. Data is the starting point from which machine learning algorithms understand patterns and correlations between variables. The models are mathematical representations of the connections between variables in the data. The data are used to train the models and provide predictions through the mathematical procedures referred to as algorithms.

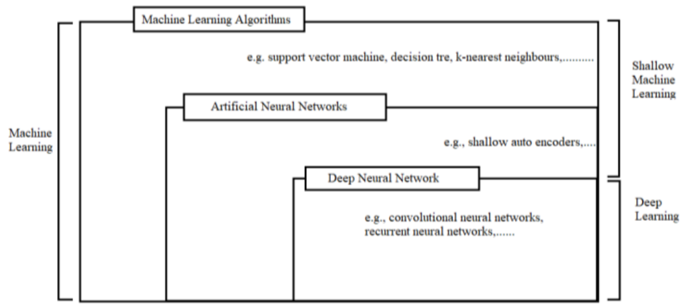

Figure 4. Machine Learning [9]

Machine learning may be a useful tool for tackling challenging problems in a range of industries, including natural language processing, medication development, speech and image recognition, among many others. Because prejudices and discrimination may be reinforced and amplified by machine learning models, it's crucial to carefully consider ethical and privacy concerns.

Artificial Intelligence:
Artificial intelligence (AI) is the capacity of robots or computer systems to do tasks that often require human intellect, such as learning, problem-solving, observation, reasoning, and decision-making. It involves the development of algorithms and computer programs that can imitate cognitive processes and behavior in humans while also improving with knowledge or experience. A few of the many AI techniques include rule-based systems, neural networks, genetic algorithms, and expert systems; each has pros and cons. Some common applications of AI include natural language processing, computer vision, machine learning, robotics, and intelligent decision-making systems. Neural networks have been successfully used to do a wide range of tasks, including image and audio recognition, natural language processing, and even playing difficult games like Go and chess. They are also used in various applications, like as medical diagnostics, autonomous cars, and voice assistants. Overall, neural networks have changed machine learning and artificial intelligence, and they have the potential to advance technology in a variety of industries going forward.

Deep Learning:
Deep learning-based artificial neural networks (ANNs), a subfield of machine learning, are simulations of the architecture and function of the human brain. A neural network can recognize patterns and relationships in the data after being trained with a large amount of data. Deep learning techniques employ many layers of artificial neural networks to extract more complex properties from the data. The output of each layer in the network is subjected to a non-linear modification. This enables the network to gain progressively high-level and abstract representations of the input as it moves through the layers. Predictive analytics, audio and picture recognition, natural language processing, and other issues have all been addressed using deep learning. TensorFlow, PyTorch, and Keras are a few well-known deep learning frameworks. Artificial neural networks can be trained to learn from a vast quantity of data and make predictions or possibilities concerning new data using deep learning, a subset of machine learning. These neural networks have numerous layers of interconnected nodes that are capable of analyzing and processing complex data, just like the human brain.

II. RELATED WORK

The universe of unending knowledge and information has undergone a great deal of prior work. Numerous authors and researchers have provided a wealth of machine learning forecasting and categorization approaches.

Radiologists may benefit from Hashmi et al.'s [10] effective method for identifying pneumonia using digital chest X-ray pictures. They present a novel weighted classifier-based strategy to combine weighted predictions from cutting-edge deep learning models, such as ResNet18, Xception, InceptionV3, DenseNet121, and MobileNetV3, in the best manner. Transfer learning improves deep learning model training and validation accuracy. Equitable training dataset expansion is achieved via partial data augmentation techniques. The suggested weighted classifier performs better than every single individual model. AUC as well as test accuracy were used when evaluating the model. On testing data from the Guangzhou Women and Children's Medical Center pneumonia dataset, the proposed weighted classifier model achieves a test accuracy of 98.43% and an AUC score of 99.76. Therefore, the suggested method may be utilized to promptly identify pneumonia and benefit radiologists in their line of work.

Convolutional neural networks (CNNs) have surpassed humans in visual identification, and artificial intelligence recognition is extraordinarily speedy, claim Zehnjia et al. [11]. They used the Kaggle dataset, which contained 5216 train images, 624 test images, and two classes: pneumonia and normal, to categorize chest X-ray images. They used five popular network techniques to categorize the pathologies in the dataset, compared the findings, and then refined MobileNet's network architecture to outperform rival approaches in terms of accuracy. The improved MobileNet network may also be expanded for use in other regions.

Zhang et al. [12] presented the CAAD (Confidence-Aware Anomaly Detection) model, which is made up of a common feature extractor, an anomaly detection module, and a confidence prediction module. The input will be classified as an anomaly case (i.e., viral pneumonia) if the confidence score calculated by the confidence prediction module is minimum enough or the anomaly score obtained by the anomaly detection module is large enough. To reinforce the one-class model, which is the main advantage of their technique over binary classification, they avoided explicitly modeling particular viral pneumonia classes and considered all reported cases of viral pneumonia as anomalies. Using the clinical X-VIRAL dataset, which contains 5,977 cases of viral pneumonia (without COVID-19) and 37,393 instances of non-viral pneumonia in healthy people or patients, the suggested method outperforms binary classification techniques. Additionally, when assessed directly on the X-COVID dataset, which consists of 106 COVID-19 cases and 107 normal controls, their model achieves an AUC of 83.61% and sensitivity of 71.70%. These outcomes are comparable to the performance of radiologists as described in the literature.

Anuja Kumar et al. [13] suggest in this study employing a deep Siamese-based neural network to automatically identify pneumonia from chest radiography pictures. Using the symmetrical structure of the two input pictures, deep Siamese-based networks compute or classify the problem. To compare the symmetrical structure and the amount of infection scattered throughout these two locations, each chest X-ray image is divided into two segments and uploaded into the network. To train and validate their model for the automatic diagnosis of different forms of pneumonia illnesses, they used the Kaggle dataset. This suggested strategy could help physicians swiftly identify pneumonia from X-ray pictures. The model beats the state-of-the-art in simulation results for all performance criteria, including decreased bias and improved generalization.

Sharma and others [14], To diagnose pneumonia, a chest X-ray image is used; however, experienced radiologists must be present. Pneumonia, COVID-19, cancer, as well as a number of other diseases, can all be identified using X-ray scans. If the illness is incorrectly diagnosed, serious problems might arise. A deep learning-based model named VGG19 is used to solve this problem by differentiating between pneumonia and healthy lungs. This study used a chest X-ray dataset of 5856 images to distinguish between pneumonia and healthy lungs. The findings were 93% accuracy, precision, recall, and F1-score with values of 0.931, 0.93, 0.931, and 0.973 for the receiver operating parameters. The performance parameters are also compared to earlier work in order to validate the new model, with the suggested model outperforming tom.

S. Urooj et al. [15] claim that TB is occasionally misdiagnosed as other conditions with comparable radiographic symptoms, leading to ineffective therapy. However, the current method is limited to use for Computer-Aided Detection (CAD) and has only been tested on models that are not deep learning models. New TB therapy options may become available thanks to deep neural networks. The method put forth in this study was intended to create a reliable method for TB detection based on stochastic learning utilizing an artificial neural network (ANN) model that utilized random fluctuations in chest X-ray images. By randomly combining the training dataset before each iteration, the proposed method would increase the parameters of an ANN model and learn features from CXR images. This would result in a variable ordering of model parameter updates. Model weights are commonly specified at a random starting point in neural networks. The suggested approach is to identify anomalies in CXR using strong or weak evidence in a variety of deep geometric settings, such as shape, size, cavitation, and density, at various TB complexity levels. Extraction of underlying linear and non-linear interrelationships of high-dimensional and complicated data is the primary advantage of ANN. The suggested method was rigorously analyzed using metrics like sensitivity, specificity, and accuracy on the Shenzhen and Montgomery datasets, and it was found that it performed more accurately than state-of-the-art methods. With sensitivity of 96.12%, specificity of 98.01%, accuracy of 98.45%, and F-Score of 95.88%, the suggested strategy demonstrates increased effectiveness.

Linh T. Duong, et al. [16] developed a technique that uses cutting-edge machine learning and computer vision techniques to diagnose TB using Chest X-Ray pictures. As the major classification engines, they developed a framework using three updated deep neural networks: modified Original Vision Transformer, improved Blended EfficientNet with Visual Transformer, and customized EfficientNet. They also employed a number of augmentation strategies to strengthen the learning process. They tested the suggested method using a substantial dataset that was built together by combining other publicly available datasets. The final dataset was divided into three sets, each of which represents 20%, 10%, and 20% of the original dataset: training, validation, and testing sets. They also evaluated their suggested strategy in comparison to two cutting-edge systems. It is encouraging that ViT_Base_EfficientNet_B1_224 achieves a maximum accuracy of 97.72% with a 100% AUC.

In the investigation suggested by S. Rajaraman et al. [17], they combine deep learning models that are tailored to certain modalities to assess the effectiveness of knowledge transfer in advancing the state-of-the-art in TB diagnosis. In order to extract modality-specific features from large, publicly available chest x-ray (CXR) collections, such as the RSNA dataset normal 8851and abnormal 17833, the Children's Pneumonia dataset normal 1583 and abnormal 4273, and the the state of Indiana dataset normal 1726 and abnormal 2378, a customized convolutional neural network (CNN) and selected renowned preconditioned CNNs are trained. The normal 326 and abnormal 336 of the Shenzhen CXR collection are used to communicate and refine the knowledge gained through modality-specific learning for TB diagnosis. When included in a stacked ensemble, the top three retrained models have promising performance accuracy of 94% at 95% confidence intervals and 95% AUC. There are no statistically significant differences in accuracy and AUC among the ensemble approaches, according to one-way ANOVA testing. The categorisation was improved by learning the pertinent features through modality-specific learning. The ensemble model decreased the sensitivity to changes in the training data as well as the prediction variance.

According to Guillaume Chassagnon et al. [18], the advancement of deep learning approaches, convolutional neural networks (CNNs) in particular have greatly surpassed more conventional machine learning techniques. Numerous uses, particularly for thoracic imaging, are now being investigated. These include the assessment of lung nodules, the detection of TB or pneumonia, or the quantification of widespread pulmonary diseases. Chest radiography is a field that lends itself nearly ideally to the development of deep learning algorithms for autonomous interpretation due to the vast volume of operations and expanding data accessibility. Current algorithms are capable of identifying up to 14 frequent abnormalities when presented as independent findings. Chest computed tomography is a significant area of application for artificial intelligence, particularly in the context of universal lung cancer screening. Radiologists must comprehend this new AI-powered future of radiology, take part in it actively, and take the initiative. For this perspective, it's important to comprehend new terms and concepts linked to machine learning. This study's goals include reporting on recent and planned advancements in thoracic imaging as well as offering useful language for understanding the techniques used and their potential. Before being used in typical clinical settings, AI technologies must be prospectively evaluated.

In the present research, Muhammad, L.J. et al. [19] used an epidemiology labeled dataset for positive and negative COVID-19 cases in Mexico to develop supervised machine learning models for COVID-19 infection using learning algorithms like logistic regression, decision trees, support vector machines, naive Bayes, and artificial neutral networks. Prior to the development of the models, the correlation coefficient analysis of numerous dependent and independent characteristics was conducted to ascertain the strength of the relationship between each dependent feature and independent feature of the dataset. The models were tested using the remaining 20% of the training dataset, which was also used to train the models. According to the findings of the performance evaluation of the models, the decision tree model has the best accuracy (94.99%), subsequent to the Naive Bayes model (94.30%) and the Support Vector Machine model (93.34%).

Cosimo Ieracitano et al. [20] suggested a fuzzy logic-based deep learning method to distinguish between CXR images of patients with interstitial pneumonias unrelated to Covid-19 and those with Covid-19 pneumonia. These CXR images are combined with fuzzy images produced using a fuzzy edge detection method to build the CovNNet model, which is then used to extract a variety of significant characteristics. In contrast to benchmark deep learning methodologies, experimental results demonstrate that mixing CXR and fuzzy features within a deep learning strategy by developing a deep network fed to a Multilayer Perceptron (MLP) led in a higher classification performance accuracy rate up to 81%. The method has been evaluated on new datasets that the virus's propagation regularly produces, and it might be helpful for patient triage in urgent situations. A basic occlusion strategy for making decisions is also suggested along with a permutation analysis.

[21], M. D. Kamrul Hasan et al. In the inquiry that was provided, it was detailed how tagged chest X-ray images were one-hot encoded using machine learning methods like Label-Binarizer and then transformed into categorical form using Python's to categorical utility. A detection model is then constructed using a variety of deep learning properties, including convolutional neural network (CNN), VGG16, AveragePooling2D, dropout, flatten, dense, and input. Adam can be used as an optimizer to predict pneumonia in COVID-19 patients. With a standard sensitivity of 95.92%, specificity of 100%, and accuracy of 91.69%, the model successfully predicted pneumonia. The model successfully increases accuracy while decreasing training loss.

III. PROPOSED WORK

Two rapidly evolving areas of artificial intelligence (AI), known as machine learning and deep learning, have showed great promise in a variety of applications, including speech recognition, picture recognition, and natural language processing. While machine learning uses algorithms and statistical models to let computers learn from data and make suggestions or judgements, deep learning uses neural networks with several layers to handle difficult tasks. In this planned endeavor, we want to investigate the performance of several machine and deep learning algorithms on a real-world dataset. focuses on building and assessing several models for a classification problem, where the goal is to predict the class label of an input instance based on its properties.

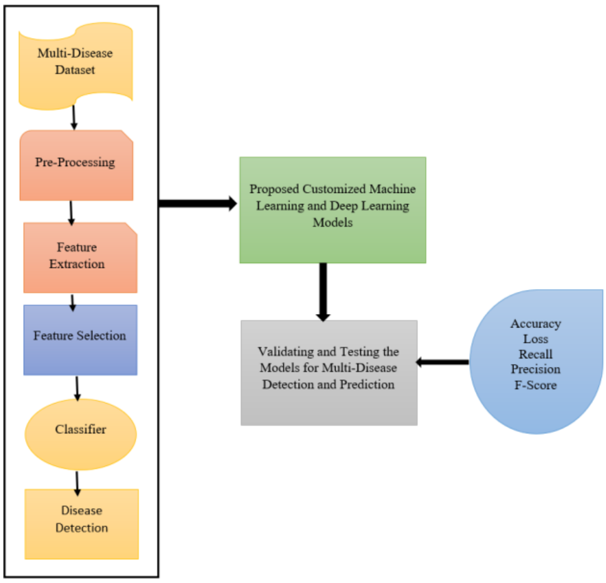

Figure 5. Multi-Disease Prediction and Classification Using Customized Machine Learning and Deep Learning Models

Multi-disease Dataset:
Each picture type in the dataset being used has its own subfolder, including Normal, Pneumonia, Covid-19, and Tuberculosis. Training datasets, testing datasets, and validation datasets are the three divisions. There are a total of 7135 chest X-ray pictures.

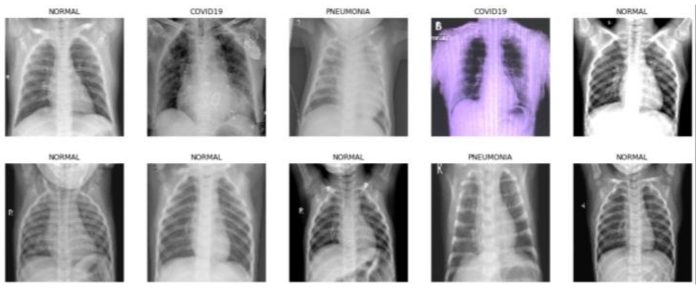

Figure 6. Dataset

On the acquired dataset, the following customized deep learning model has been implemented.

CNN:

CNN is a subset of deep learning model that can comprehend data with a grid pattern, such as images, according to Yamashita et al. [22]. CNN was created with the animal visual cortex in mind to automatically and adaptively acquire spatial hierarchies of properties, from low-level to high-level patterns. A typical CNN is made up of three different layer types: convolution, pooling, and fully connected. Convolution and pooling are the first two layers that extract features; the third layer, fully connected, is what converts the extracted features into the desired output, such as classification. In CNN, which is made up of a number of mathematical operations, including convolution, a specific kind of linear operation, a convolution layer is crucial. Because a feature could potentially be present everywhere in a digital image, pixels are stored in a two-dimensional grid, or array of integers, and a kernel, or optimizable feature extractor, is applied at each location in the image. As a result, CNNs are excellent at processing images. The complexity of retrieved features may gradually and hierarchically increase as one layer feeds its output into the following layer. Training is the process of minimizing the difference between outputs and ground truth labels through the application of optimization techniques like backpropagation and gradient descent, among others. It entails enhancing variables like kernels.

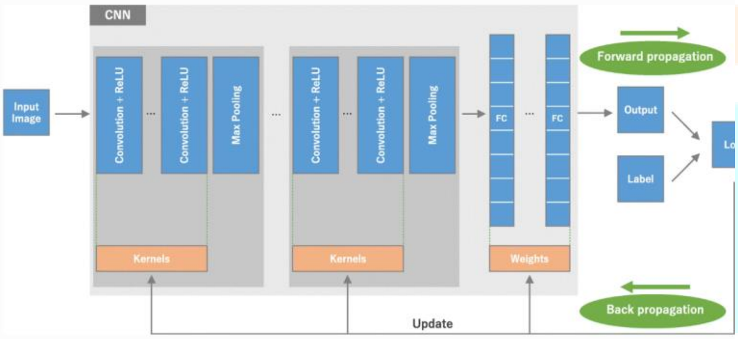

Figure 7. Building Block of CNN Architecture [23]

EfficientNet:

EfficientNet is a family of convolutional neural networks (CNNs) designed to achieve high accuracy on image classification tasks while being computationally economical. EfficientNet's design was created by methodically increasing the depth, breadth, and resolution of the neural network, allowing it to attain great accuracy while keeping the processing cost relatively cheap. The EfficientNet design is based on a compound scaling strategy, in which the neural network's depth, breadth, and resolution are scaled concurrently to improve performance. expanding the depth of the network by adding additional layers, expanding the breadth of the network by increasing the number of filters in each layer, and scaling the resolution of the input picture are all part of this strategy. By methodically adjusting these settings, EfficientNet outperforms other state-of-the-art CNN systems in terms of accuracy and computation efficiency. The smallest and quickest EfficientNet-B0 model and the biggest and most precise EfficientNet-B7 model are both available in a range of sizes. The ImageNet dataset, which contains more than a million pictures categorized into 1000 categories, was used to train the models. In a range of computer vision tasks, including image classification, object recognition, and segmentation, EfficientNet has proven to be extremely accurate. It is a well-liked option for applications with constrained computing capabilities, including mobile devices or embedded systems, because to its effectiveness and accuracy.

Inception-V3:

In the Large-Scale ImageNet Visual Identification Challenge 2014, Szegedy et al. [24] suggested the Inception model, a deep CNN architecture, to counteract the impacts of processing efficiency and low parameters in application scenarios. The primary objective of the Inception architecture is to investigate how a convolutional vision network's ideal local sparse structure may be approximated and covered by readily accessible dense components. Remember that assuming translation invariance entails employing convolutional construction pieces to form our network. All that is needed is to identify the finest local building and spatially replicate it. Arora et al. [25] recommended looking at the preceding layer's correlation data and grouping the units into clusters with strong correlation. The units of the subsequent layer are created by connecting these clusters to the units in the preceding layer. Assuming that each unit from the previous layer maps to a distinct region of the input picture and that the units from the previous layer are arranged into filter banks. Correlated units would cluster in a few spots in the bottom layers, particularly those close to the input. This suggests that there would be several clusters grouped together in one location, which might be covered by a layer of 11 convolutions in the layer below, as shown in [26]. The source picture size for Inception-v3 was 299 299 pixels, according to Cao J. et al. [27]. Inception-v3 outperforms VGGNet despite being 78% larger (244 244) and running at a quicker pace. The main justifications for Inception-v3's outstanding efficacy are as follows: Compared to AlexNet's (60,000,000) parameters, Inception-v3 contains less variables than one-fourth of VGGNet's (140,000,000). Additionally, Inception-v3 is more powerful than Inception-v1 since it does about 5,000,000,000 more floating-point computations overall than Inception-v1. These additions increase the utility of Inception-v3 by making it simple and quick to incorporate into a shared server.

Resnet:

ResNet, or "Residual Network," is a deep learning architecture that has had a considerable impact on computer vision applications including object identification and picture categorization. Kaiming He et al. [28] first described it in their research "Deep Residual Learning for Image Recognition" from 2015. Traditional deep neural networks are impacted by the vanishing gradient problem, which happens when gradients spread over several layers and are very tiny. The network's depth is constrained by this issue, which also hinders appropriate learning. To address this problem, ResNet offers a ground-breaking concept called residual learning. In ResNet, the fundamental building block is the residual block. One or more convolutional layers and an identity shortcut link are the two main components of a residual block. The convolutional layers learn the residual mapping, which represents the difference between the desired output and the block's current output. The primary goal of an identity shortcut connection is to provide a skip connection that rapidly propagates an input block's data to an output block. By doing this, the network may learn to alter the residual mapping rather than learning the entire mapping from scratch. As a result, the network may be able to effectively learn the necessary transformation even with a tiny mapping. The remaining building pieces are stacked on top of one another to

Model: "classifier"

Layer (type)	Output Shape	Param #
block1_conv1 (Conv2D)	(None, 128, 128, 32)	896
block1_conv2 (Conv2D)	(None, 128, 128, 32)	9248
pool1 (MaxPooling2D)	(None, 64, 64, 32)	0
block2_conv1 (Conv2D)	(None, 64, 64, 64)	18496
block2_conv2 (Conv2D)	(None, 64, 64, 64)	36928
pool2 (MaxPooling2D)	(None, 32, 32, 64)	0
block3_conv1 (Conv2D)	(None, 32, 32, 128)	73856
block3_conv2 (Conv2D)	(None, 32, 32, 128)	147584
pool3 (MaxPooling2D)	(None, 16, 16, 128)	0
flatten (Flatten)	(None, 32768)	0
dropout1 (Dropout)	(None, 32768)	0
dense1 (Dense)	(None, 128)	4194432
final (Dense)	(None, 4)	516

Total params: 4,481,956
Trainable params: 4,481,956
Non-trainable params: 0

form deep networks with hundreds or thousands of layers. The skip connections, which enable gradients to move right across the network without disappearing, make it easier to train very deep models. Deeper networks have been shown to collect qualities that are more abstract and complex, enhancing performance on a number of tasks. ResNet designs come in a variety of forms, such as ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152. The number in the graphic indicates all of the network layers. The deeper variants require more computer power during training, despite the fact that they frequently perform better.

VGG:

The VGG (Visual Geometry Group) deep convolutional neural network architecture was presented in 2014 by academics at the University of Oxford. It is a reference to the Visual Geometry Group, the research organization where it was developed. It is also known as the VGGNet, and it has become well-known for both how simple it is to use and how effective it is in categorizing images. Utilizing a succession of small convolutional filters (3x3) with a stride of 1, which successfully captures and learns local spatial patterns, is the main principle behind VGGNet. VGGNet has shown outstanding performance on a variety of photo classification challenges, including the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). However, VGGNet's use in situations with limited resources is constrained by its high processing cost as a result of its various parameters. VGGNet has still made significant contributions to the area of deep learning and served as a basis for following designs, influencing the development of other well-known CNN models like ResNet and DenseNet. In general, the VGGNet design principles of simplicity, depth, and small filter size have demonstrated the importance of depth and local spatial patterns in convolutional neural networks, leading to advancements in feature learning and picture classification. The VGG16 design is well known for being both uncomplicated and effective. There are 16 layers total, including 13 convolutional layers and 3 completely connected layers. Convolutional layers work to extract information from the input picture whereas fully linked layers operate as a classifier.

Figure 8. Summary of VGG-16 Model

IV. RESULTS AND ANALYSIS

For Prediction and classification, the dataset contains Chest X-ray images of multiple diseases such as Pneumonia, Tuberculosis, COVID19 and Normal Images has been used. A total of 7135 Chest X-ray images are present in the dataset.

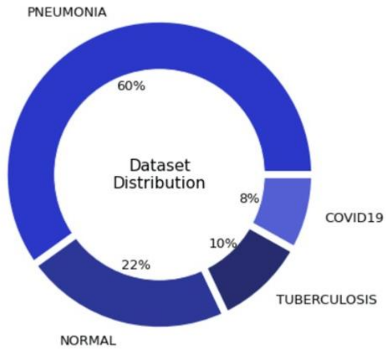

Figure 9. Dataset Distribution

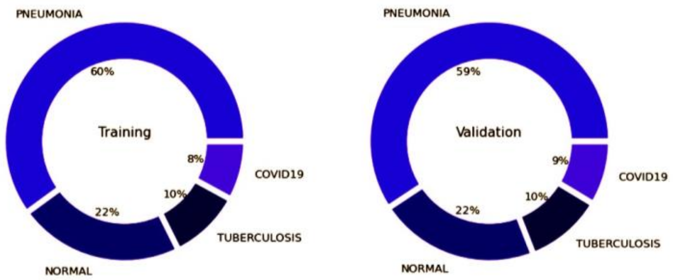

Figure 10. Data Categorization as Training and Validation Datasets

When a model is trained on this incredibly imbalanced dataset, it will overfit the class that is overrepresented while failing to pick up patterns from other classes. Fortunately, there are solutions to this problem, and what we'll be doing is assigning the classes "class weights" to address it. A bias in favor of the dominant class will result from the use of the cross-entropy loss function. Therefore, multipliers or "weights" will be utilized to balance the loss function.

Utilizing the supplied dataset and the Convolutional Neural Network, it was possible to obtain 99% training accuracy and 82% testing accuracy. The convolutional neural network model's findings are shown in the following tables.

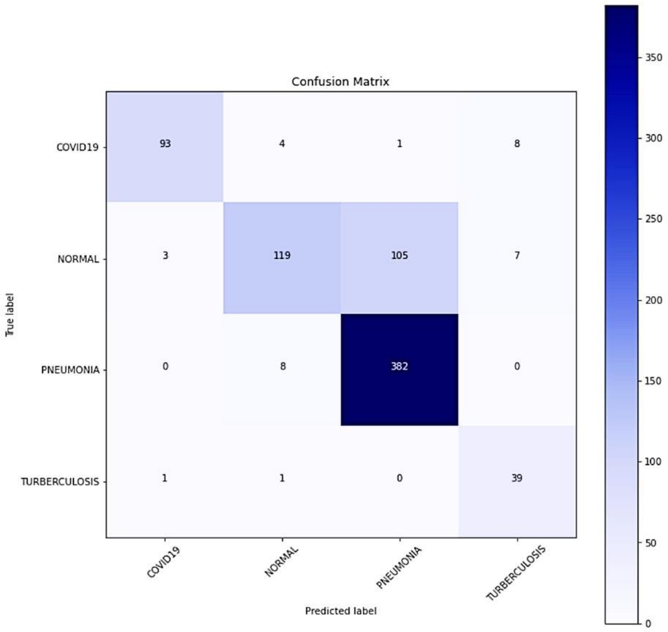

Figure 11. Confusion Matrix for Prediction and Classification of Multiple Disease Using CNN

Using the provided dataset and the Inception-V3 implementation, it proved conceivable to obtain 92% training accuracy and 86% testing accuracy. The outcomes of the Inception-V3 are shown in the following figures.

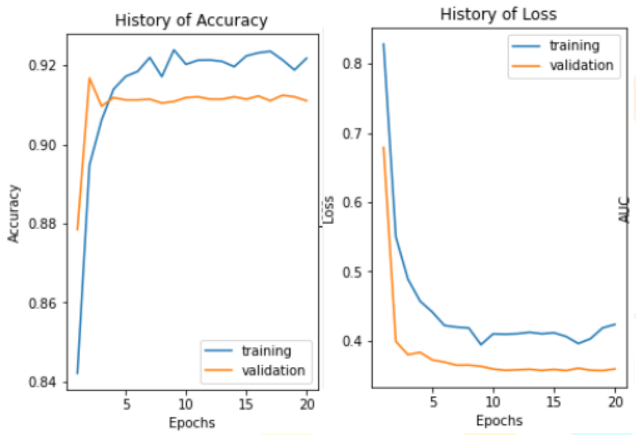

Figure 12. History of Accuracy and Loss w.r.t. training and validation dataset Implementing InceptionV3

By implementing the EfficientNetB0 using the available dataset abled to achieve the 98% validation accuracy and the Testing Accuracy of 91%. The following graphs represents the results of the EfficientNetB0.

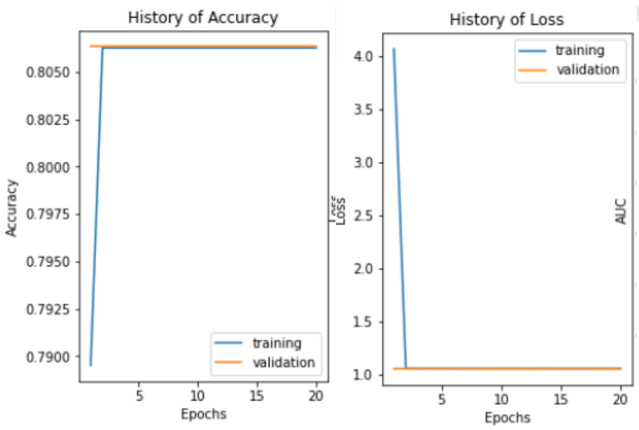

Figure 13. History of Accuracy and Loss w.r.t. training and validation dataset Implementing EfficientNetB0

Through combining the provided dataset with Resnet152V2, it was possible to obtain testing accuracy of 92% and validation accuracy of 97%. The Resnet152V2 findings are shown in the following.

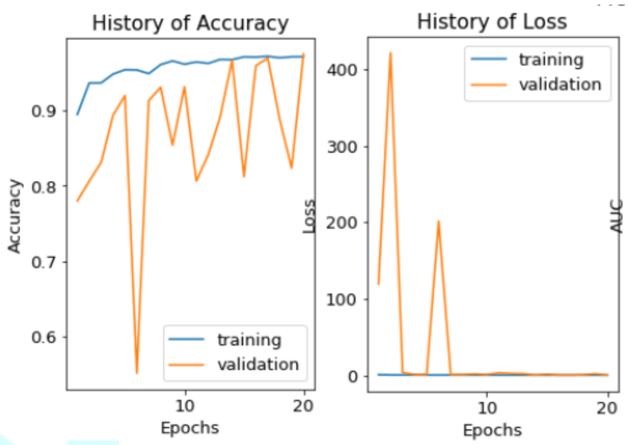

Figure 14. History of Accuracy and Loss w.r.t. training and validation dataset Implementing Resnet152V2

By implementing the VGG-16 using the available dataset abled to achieve the 95.7% validation accuracy and the Testing **Accuracy** of **95.3%**. The following figure represents the results of the VGG-16.

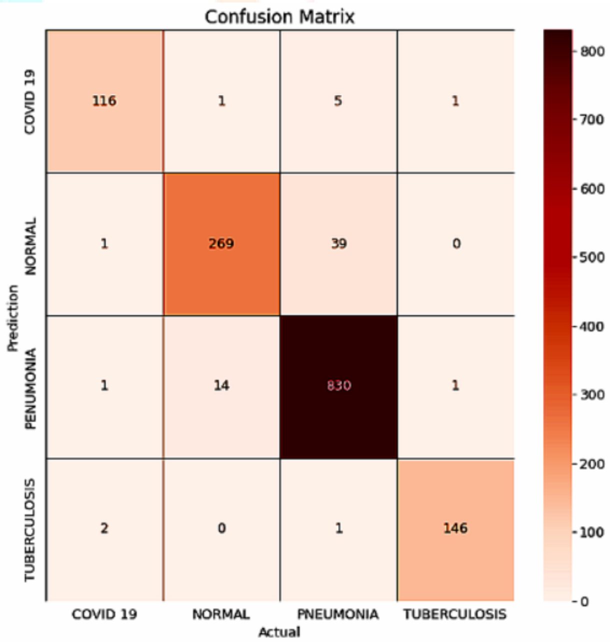

Figure 15. Confusion Matrix for Prediction and Classification of Multiple Disease Using CNN

Table 2. Results

Model	Accuracy	Precision	Recall	F1-Score
CNN	82%	96%	88%	92%
InceptionV3	86%	76%	72%	71%
EfficientNetB0	91%	82%	81%	82%
Resenet152V2	92%	84%	84%	85%
VGG16	95%	96%	97%	96%

Since VGG16 showed the best results, here are some successful classification and prediction of Multiple Chest X-ray Diseases.

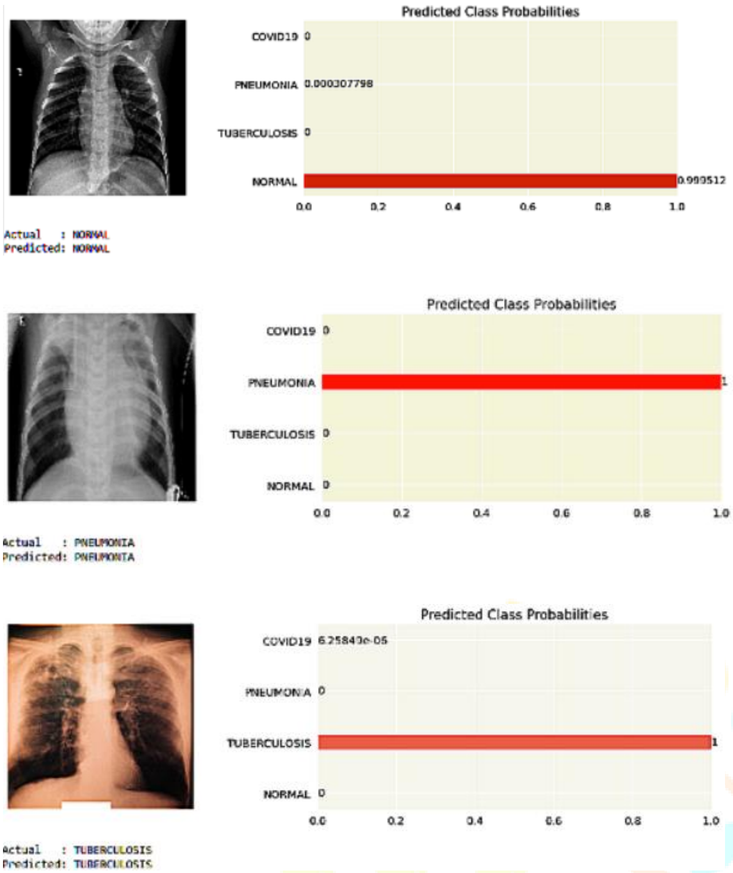

Figure 16. Prediction and Classification of Multiple Disease using VGG-16

V. CONCLUSION AND FUTURE SCOPE

The development and use of a multi-disease prediction and classification model using deep transfer learning techniques has produced positive results in the field of medical diagnostics. This state-of-the-art approach accurately predicts and categorizes various illnesses from a range of medical datasets with the use of pre-trained models and the power of deep learning algorithms. In the study that is being presented, we employed a variety of deep learning models, including Resnet, CNN, EfficientNetB0, InceptionV2 and VGG16, however the VGG16 findings outperformed the others with a 95% accuracy rate. The accessibility of large medical datasets, as well as continuous advancements in deep learning and transfer learning methods, all promote the potential scalability and flexibility of these models in actual healthcare settings. When fresh information becomes available, the model may be further modified, improving performance.

Deep transfer learning algorithms have a lot of potential for multi-disease prediction and classification in the future of the healthcare sector. Enhanced Accuracy, Multi-Modal Data Integration, Early Detection and Prevention, and Diagnosis of Rare Diseases are some critical areas for future development and use.

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