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Lung Disease Classification Using Deep Learning Models from Chest X-ray Images

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***Abstract*—In the very recent past, Infectious disease-related sickness has long posed a concern on a global scale. Each year, COVID-19, pneumonia, and tuberculosis cause a large number of deaths because they all affect the lungs. Early detection and diagnosis can increase the likelihood of receiving quality treatment in all circumstances. A low-cost, simple imaging approach called chest X-ray imaging enables to detection and screen lung abnormalities brought on by infectious diseases for example Covid-19, pneumonia, and tuberculosis. This paper provided a thorough analysis of current deep-learning methods for diagnosing Covid-19, pneumonia, and TB. According to the research papers reviewed, Deep Convolutional Neural Network is the most used deep learning method for identifying Covid-19, pneumonia, and TB from chest X-ray (CXR) images. We compared the proposed DNN to well-known DNNs like EfficientNetB0, DenseNet169, and DenseNet201 in order to more accurately assess how well it performed. Our findings are equivalent to the state-of-the-art, and since the proposed CNN is lightweight, it may be employed for widespread screening in areas with limited resources. From three diverse publicly accessible datasets merged into one dataset, the suggested DNN generated the following precisions for that dataset: 99.15%, 98.89%, and 97.79% for EfficientNetB0, DenseNet169, and DenseNet201 respectively. The proposed network can help radiologists make quick and accurate diagnoses because it is effective at identifying COVID-19 and other lung contagious disorders utilizing chest X-ray images. This paper also gives young scientists a good insight into how to create CNN models that are highly efficient when used with medical images to identify diseases early.**

***Index Terms*—Lung Disease, COVID-19, Pneumonia, Tuberculosis, X-ray Image**

I. Introduction

Deep learning models have recently become a potentially beneficial tool in healthcare for diagnosing disorders, such as lung ailment which is the focus of this work. Deep learning models have shown encouraging results in assessing different medical problems [1]. The healthcare industry is able to perform data analysis at breakneck speeds without sacrificing accuracy as a result of this capability [2]. CNN is a deep learning approach often employed to interpret medical images for fast and accurate decision-making. The goal behind medical image analysis is to aggregate medical images to create a CNN evaluation that can differentiate between chaos and relevant clinical results [3]. COVID-19 has resulted in the application of deep learning in several contexts. This includes the capacity to anticipate overall instances as well as identify COVID-19 through coughing noises or visual data, which includes X-rays or CT scans [4]. In December 2019, the initial COVID-19 verified incidence was found in Wuhan, which is located within the Hubei region of China, From there, this virus began to spread to other nations all over the world [1]. The virus which is causing Covid-19 and spreading the sickness is named SARS-CoV-2 virus. Most infected people simply develop a mild respiratory infection and heal without treatment. However, a few people will develop serious illnesses and need prescribed treatment. Older adults or those with diabetes, coronary heart conditions, respiratory infections, or cancer have an increased risk of having a serious medical condition than younger people without these problems [5]. Fast diagnosis of COVID-19-infected persons and specialized care and therapies are the most effective ways to tackle the outbreak. RT-PCR is often used to diagnose COVID-19, however, this becomes resistant to such virus in its initial phases, resulting in further viral propagation [6]. Chest X-ray pictures and Computed tomography scanners are the most reliable methods for identifying patients exhibiting signs of pneumonia because the test kit is pricey and hard to come by [1]. A radiographic investigation, adequate microbiological problems, and clinical awareness are all necessary components in the diagnostic process for lung infection [7]. In addition to reviewing the patient's symptoms when they arrive at a medical facility, a number of diagnostic procedures, including X-rays, are performed. The state of the lungs and the progression of the disease can be more precisely evaluated using X-ray pictures.

The major contributions of the presented manuscript are:

- Those suggested models are capable of classifying lung diseases for testing data with tremendous results.
- The proposed model is regarded as the result of a Deep Convolutional Neural Network(DCNN).

II. LITERATURE REVIEW

Mehta & Mehendale [8] gathered 1229 images from COVID-Mild, COVID-Medium, COVID-Severe, Normal, Pneumonia, and Tuberculosis categories. cGAN was used to increase the number of pictures, and ResNet50, Xception, and DenseNet-169 were trained to correctly classify them. Training and validation accuracy was 98.20% and 94.21%,

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respectively. Test accuracy was 93.67% for the model. Khan et al. [3] recommended using CoroNet to find COVID-19 on chest X-rays. The model was trained with ImageNet and 1300 COVID-19 and chest pneumonia X-rays from two public datasets. CoroNet acquired an accuracy of 89.6% for four classes (COVID vs Pneumonia bacterial vs pneumonia viral vs normal patients) and 95% for three classes (COVID versus Pneumonia versus normal cases). Abiyev & Ismail [1], suggested two distinct CNN models. The first model was trained on pneumonia patients and normal CXRs. The second model was trained with COVID-19, pneumonia, and normal 2nd Chest Xray pictures. The model achieved 98.3% accuracy, 97.9% recall, 98.3% precision, and 98.0% F1 score.

Yoo et al. [9] used a decision tree classifier that leverages deep learning to locate COVID-19 in CXR images. First, CXR images were divided into normal and pathological. The 2nd tree found anomalous TB images, while the 3rd tree did so for COVID-19. The 1st and 2nd decision trees were 98% and 80% accurate, accordingly. The 3rd tree was 95% accurate. Subramaniam et al. [10] suggested a preprocessing and classification technique for identifying lung diseases. X-ray images were segmented using HOG, Haar, and LBP. Preprocessed X-rays identify normal, COVID-19, and pneumonia better than raw images. They employed VGGNet, AlexNet, Resnet, and a DNN to classify respiratory diseases. Findings suggest that DNN outperforms other classification models.

Venkataramana et al. [2] employed a multistage classification system on chest X-rays to help doctors make more accurate diagnoses of tuberculosis and pneumonia. Tuberculosis and pneumonia classification accuracy was 97.4% and 88% after training. Multilevel classification improves accuracy by 8-10% over current methods. Marginean et al. [4] discovered COVID-19 changes in chest X-rays using parabolic and hyperbolic CNNs and transfer learning. They trained parabolic and hyperbolic networks on normal and pneumonia images to tell COVID-19, pneumonia, TB, and normal apart. Comparing COVID-19 network adaptations they concluded Quantitative and qualitative studies show more trustworthy networks.

Chen [11] created an accurate classification strategy for detecting COVID-19 viral patterns using chest x-rays and HOG feature extraction. The recommended system employs Cohen's dataset, which comprises 60000 photographs and 400 positive chest x-ray images of covid-19. The proposed approach works effectively with minimal COVID-19 data and finds unique input features inside classes. Alakus & Turkoglu [12] combined deep learning and lab data to develop clinical predictive models to estimate COVID-19 disease risk. The algorithms' accuracy was proven using 10-fold cross-validation and train-test split approaches on 18 lab data from 600 patients. Experiments demonstrate that their prediction models can find COVID-19 disease with 86.66% accuracy, 91.89% F1-score, 86.75% precision, 99.42% recall, and 62.50% AUC score.

Horry et al. [13] used transfer learning from deep learning models for detecting COVID-19 in X-Ray, Ultrasound, and CT scan images. The chosen VGG19 model detects COVID-19 against pneumonia or normal for all three lung imaging methods with 86% accuracy for X-Ray, 100% for Ultrasound, and 84% for CT scans. Mahbub et al. [14] developed a lightweight (9-layered) DNN to identify lung disorders using chest x-ray images caused by Covid-19, Pneumonia, and Tuberculosis. The recommended deep learning network was 99.87% accurate in the Covid-19 vs healthy dataset, 99.55% in the Pneumonia dataset, and 99.76% in the Tuberculosis dataset. Non-healthy CXR screening accuracy was 98.89% for Covid-19 vs Pneumonia, 98.99% vs tuberculosis, and 100% vs Pneumonia.

Mamalakis et al. [15] developed DenResCov-19 using chest X-ray images to detect COVID-19, pneumonia, TB, and healthy patients. They tested their proposed network on two-, three-, and four-class classification issues (COVID-19 positive, healthy, pneumonia, and TB). Findings suggest that AUC-ROC is 99.60%, 96.51%, 93.70%, and 96.40% for Datasets DXR1, DXR2, DXR3, and DXR4. M. Zak and A. Krzyżak [6] used VGG16, ResNet-50, and InceptionV3 for lung disease categorization. They created a pipeline to isolate CXR pictures before classification and compared it to current frameworks. They tested their methods on Shenzhen and Montgomery lung disease datasets. InceptionV3 model tied with top Shenzhen response while being cheaper.

Bharati et al. [17] created a hybrid deep learning system which is a combination of VGG, data augmentation, and STN. They used a dataset of chest X-rays collected from Kaggle's NIH. VDSNet's full dataset validation accuracy is 73%, whereas vanilla gray, vanilla RGB, hybrid CNN and VGG, and modified capsule network are 67.8%, 69%, 69.5%, and 63.8%. ResNet50 and DenseNet were employed by Anitha et al. [18] to diagnose lung illnesses. The accuracy rates for the ResNet50 and DenseNet models are encouraging: 86.67 and 98.33%, respectively. Deng et al. [19] recommended using MobileNetV2 to predict lung illnesses from frontal thoracic X-rays. Using the NIH Chest-Xray-14 database, they compared their technique to other cutting-edge classification methods. They got an average AUC of 0.811 and an accuracy of around 90%. Magrelli et al. [20] trained four deep-learning models to identify bronchiolitis and pneumonia in babies. They collected 5,907 photographs using a public dataset and worked on the disease in two sections. They employed VGG19, Xception, Inception-v3, and Inception-ResNet-v2 algorithms and got accuracy with 92.25%, 95.25%, 93.5%, and 97.75%.

III. RESEARCH METHODOLOGY

Figure 1 shows the working procedure of this research, starting with data collection and then dataset ready and so on.

A. Data Collection

In this study, we used three publicly available dataset of chest x-ray images from mendeley data [21], IEEE Dataport [4], covid-chestxray-dataset [22] to classify images of covid-19, tuberculosis, pneumonia and healthy classes. We've created a dataset by combining collecting data from various

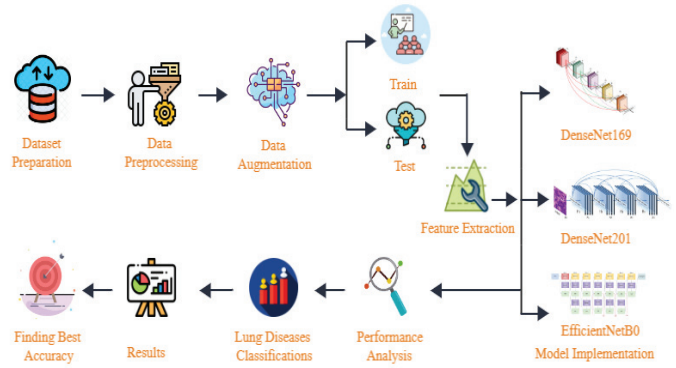

Fig. 1. Working Procedure Diagram

sources and produce a final dataset with 4 classes which are Covid-19, Pneumonia, Tuberculosis and Normal. Here are some sample images of those classes –

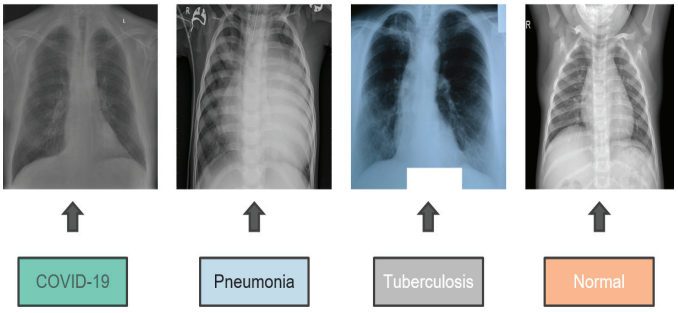

Fig. 2. Sample images from dataset

B. Data Preprocessing

To increase the model precision, it is essential to preprocess the clinical data in order to retrieve the relevant info and eliminate any extraneous information [23] . Our data collection contains images of varying sizes, posing a difficulty for training purposes. As a result, we have altered the proportions of the image to (224,224). All photos are converted to RGB and jointly analyzed for different models. We rescaled the images and changed the class mode to categorical because none of the images in our dataset were scaled.

C. Data Augmentation

The issue of insufficient information can be remedied by the use of an alternative method known as data augmentation. In our dataset we applied specific picture modifications, 3 channel color photos and tagged them in the data pre-processing phase (RGB). We were therefore capable of training the dataset using higher-quality photos and see improved performance [24]. We have also used flipping two times, shuffle, resizing and converted our images mode to categorical in order to achieve the desired results.

D. Fine Tuning

A procedure that is frequently referred to as ”fine-tuning” may be used to improve the functionality of a function. A few very few changes that are performed at various points along the process improve the final product. We repeated the fine-tuning procedure several times and tested a wide range of alternative parameter values since we wanted our model to be as accurate as possible. Table I provides an overview of the factors that can be changed during those processes and lists the training and adjustment techniques that produce the best outcomes.

TABLE I
MODELS FINE TUNING WITH PARAMETERS

Parameter	Value
Batch Size	30
Steps Per Epoch	50
Epoch	30
Optimizer	Adam, Adamax
Activation Function	Softmax, Relu

E. Model Implementation

In order to determine the model that would be best for our research, we concentrated on models that are mostly used, are suitable for transfer learning, and are readily available in packaged form from trustworthy public libraries such as Keras. As a result, we examined only representations of the essential models applicable to this field, as will be detailed in greater detail below. All of these models are conveniently accessible via the Keras Application Programming Interface (API), and they all support transfer learning [25] by enabling the pre-application of ImageNet [26] weights to the model.

1) EfficientNetB0: Instead of being designed by engineers, the EfficientNet-B0 architecture was created by the neural network itself. They arrived at this model by searching for a multi-objective neural network that simultaneously maximizes accuracy and optimizes floating-point operations. The authors created a full family of EfficientNets, ranging from B1 to B7, with B0 acting as the series' foundational model. B0 is an easily transportable architecture with eleven million trainable parameters [19]. Unlike other kinds of DCNNs, EfficientNetB0 scales each dimension using a specified set of scaling parameters. This technique considerably outperformed earlier state-of-the-art models that were trained on the ImageNet dataset [27]. Figure 3 illustrates the architecture of EfficientNetB0.

2) DenseNet169: The Densenet-169 model, constructed by G. Huang et al., won the 2017 ImageNet competition [28]. The feature maps of every layer after it in Densenet receive data from all layers before it. Each layer collects data from the hierarchy above it. Because each layer collects feature maps from all layers before it, the network may be more compact and have fewer channels and hence improving computational and memory efficiency. The Densenet-169 architecture is shown in Figure 4.

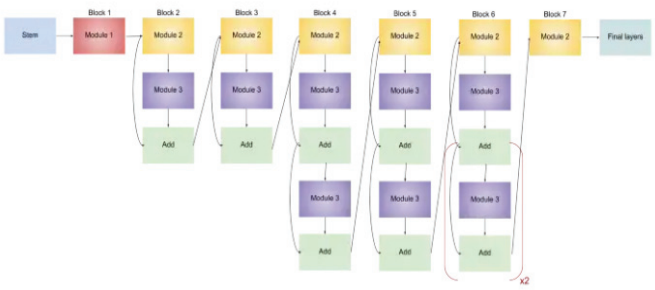

Fig. 3. Architecture of EfficientNetB0

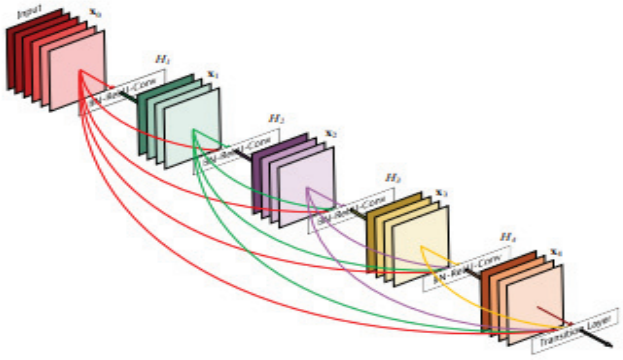

Fig. 4. Architecture of DenseNet169

3) DenseNet201: DenseNet201's architecture makes it possible to build models that are easy to build and understand. Reusing features across levels improves the architecture's parameters and allows the following layers to have a bigger variety of functions and better performance. A feed-forward system links one layer of the design to the next. Additionally, the DenseNet201 model has a bottleneck structure and a pooling layer. If the model is simplified and the number of property components is reduced, this architecture may perform better [28]. Figure 5 displays the architecture of EfficientNetB0.

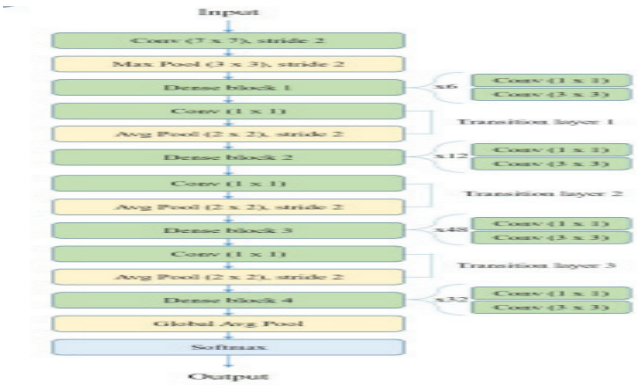

Fig. 5. Architecture of DenseNet201

F. Model Training

In this experiment, the TensorFlow framework has been implemented for training purposes. Utilizing Adam and Adamax [29] optimizers has allowed for greater optimization. To increase memory consumption, we trained the DenseNet-201, DenseNet-169, and EfficientNetB0 models with a total of 30 distinct batch sizes including model fine-tuning.

IV. RESULTS AND DISCUSSIONS

To accomplish our experimental study, we choose three lung diseases and a healthy lung class to implement the transfer learning model. They are Covid-19, Pneumonia, Tuberculosis, and Normal or healthy lungs. We have implemented three(3) pre-trained transfer learning models and they are EfficientB0, DenseNet169, and DenseNet201.

The initial step we followed is to image acquisition. To train the model several steps are constructed as image preprocessing run to resize, filter, image augmentation, and so many others. We utilized a total of 6340 images for the entire experiment while we divided our data into three sections with an 80:15:5 ratio where 5072 images has been used to train the model and 951 images were used for the testing model to predict and 317 for validation to classify the diseases.

For the performance measure of the applied three-transfer learning model, we evaluated the confusion matrix [30] for each class which is an effective way to find the appropriate model for the classification task. The confusion matrix for three applied three models is presented in Figure 6.

After that, for the class-wise performance of three models, The True-positive (TP), False-negative(FN), False-positive(FP), and True-negative(TN) are also considered in regard of find an optimal model for this study and we also computed other performance measurements such as accuracy, precision, recall, TPR, TNR, FPR, FNR, and f1 score to find out the best model.

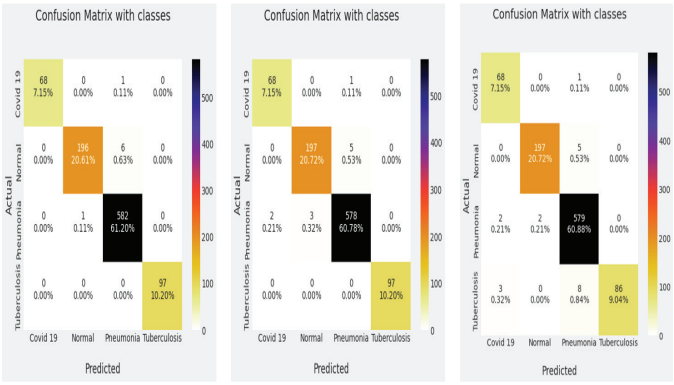

Fig. 6. Confusion matrix for (a) EfficientB0, (b) DenseNet169 and (c) DenseNet201.

A. For EfficientNetB0

Figure 7 represents the accuracy and loss graph for the EfficientNetB0 model which indicates minimal validation loss occurred in the 30th epoch and provide maximum validation

accuracy in the 17th epoch. The outcomes of the EfficientNetB0 classifier's class-by-class evaluation metrics are shown in Table II for each disease class. It has been noted that the classifier EfficientNetB0 attained the highest accuracy of 99% while classifying the Tuberculosis class. In comparison to other classes, TPR, FNR, FPR, TNR, precision, and F1 Score for the Tuberculosis class are, 10.20%, 0%, 0%, 88.96%, 100%, and 100%, respectively.

Fig. 7. Training & Validation Loss and Training & Validation Accuracy for EfficientNetB0

TABLE II
CLASS-WISE PERFORMANCE METRICS FOR EFFICIENTNETB0 MODEL

Model	Class	Precision	Recall	F1-Score	Accuracy
EfficientNetB0	Covid-19	1.00	0.99	0.99	0.99
	Normal	0.99	0.97	0.98	
	Pneumonia	0.99	1.00	0.99	
	Tuberculosis	1.00	1.00	1.00	

B. For DenseNet169

Figure 8 represents the accuracy and loss graph for the DenseNet169 model which indicates minimal validation loss occurred in the 30th epoch and provides maximum validation accuracy in the 30th epoch. The outcomes of the DenseNet169 classifier's class-by-class evaluation metrics are shown in Table III for each disease class. It has been noted that the classifier DenseNet169 attained the highest accuracy of 99% while classifying the Tuberculosis class. In comparison to other classes, TPR, FNR, FPR, TNR, precision, and F1-Score for the Tuberculosis class are, 10.20%, 0%, 0%, 88.65%, 100%, and 100%, respectively.

TABLE III
CLASS-WISE PERFORMANCE METRICS FOR THE DENSENET169 MODEL.

Model	Class	Precision	Recall	F1-Score	Accuracy
DenseNet169	Covid-19	0.97	0.98	0.99	0.99
	Normal	0.98	0.98	0.98	
	Pneumonia	0.99	0.99	0.99	
	Tuberculosis	1.00	1.00	1.00	

C. For DenseNet201

Figure 9 represents the accuracy and loss graph for the DenseNet201 model where it indicates minimal validation

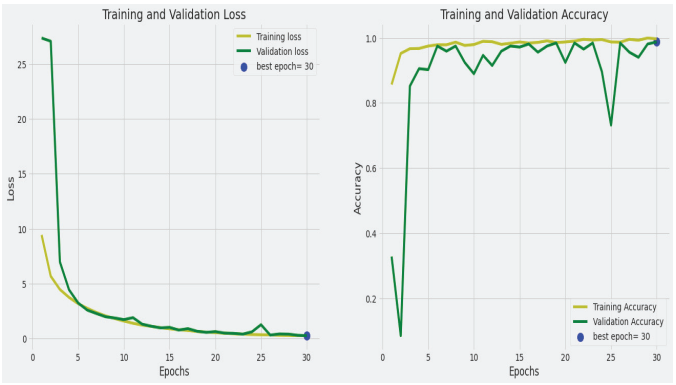

Fig. 8. Training & Validation Loss and Training & Validation Accuracy for DenseNet169

loss occurred in 25th epoch and provide validation maximum accuracy in 19th epoch. The outcomes of the DenseNet201 classifier's class-by-class evaluation metrics are shown in Table IV for each disease class. It has been noted that the classifier DenseNet201 attained the highest accuracy of 98% while classifying the Pneumonia class. In comparison to other classes, the TPR, FNR, FPR, TNR, precision, and F1 Score for the Pneumonia class are, 60.88%, .42%, 1.48 36.91%, 98%, and 99%, respectively.

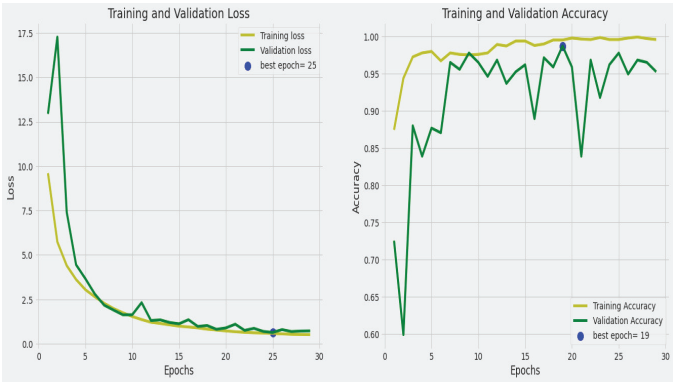

Fig. 9. Training & Validation Loss and Training & Validation Accuracy for DenseNet201

TABLE IV
CLASS-WISE PERFORMANCE METRICS FOR DENSENET201 MODEL.

Model	Class	Precision	Recall	F1- Score	Accuracy
DenseNet201	Covid-19	0.93	0.99	0.96	0.98
	Normal	0.99	0.98	0.98	
	Pneumonia	0.98	0.99	0.99	
	Tuberculosis	1.00	0.89	0.94	

The outcome achieved by our suggested model is quite remarkable. The levels of accuracy achieved by EfficientNetB0, DenseNet169, and DenseNet201 were respectively 99.15%, 98.84%, and 97.79%. Table V shows the comparison between our proposed model with other existing models to classify lung diseases.

TABLE V
COMPARATIVE ANALYSIS OF OUR PROPOSED MODEL WITH PREVIOUS WORKS

Algorithms	Accuracy (%)	Dataset
Inception+ResNet V2 [31]	92.18%	Public
VGG-19 [32]	98.75%	Public
DeTrac [33]	95.12%	Public
Xception+ResNet50 [[34]	91.40%	Public
ResNet50 [35]	98.00%	Public
ResNet-152 + DenseNet-121 [36]	98.43%	Public
Proposed	**99.15%**	**Public (3 Datasets Combined)**

V. CONCLUSION

AI will usher in the fourth industrial revolution by enabling us to write programs more quickly. AI will thus be the era of the future. We won't be able to come up with any fresh ideas without AI. Everything will be automated with the aid of AI. We employed DNN and image processing in our study, and we believe that this will benefit those industries. Our research helps us develop knowledge and skills in the field of artificial intelligence while also advancing our grasp of deep learning techniques. The study provides ideas on how to address various image classification issues and extract characteristics from image files. While conducting the research project, we faced a number of challenges. Images need more time and complexity to process than text or any other sort of data. High-end picture file handling tools are therefore necessary, but they are also rather expensive. It was challenging for us to collect these X-ray images. It was challenging for us to identify and collect validated data, so we used a variety of trustworthy sources. It was quite difficult for us to process the obtained data and feed the model without such inputs. To obtain excellent accuracy, we had to analyze the accuracy of several models, which required a lot of time.

This research will be expanded in order to create a web application that will automate the disease identification process, thereby saving both time and money. Using this technology, physicians can examine the chest x-ray to determine if their conclusion was accurate. It can only aid physicians in making decisions; only an expert can make the final determination. Patients can also use the tool to determine if they have Covid-19, pneumonia, or Tuberculosis by downloading an X-ray image. They merely need to follow the doctor's instructions and, after the application identifies pneumonia, take the appropriate prescriptions. This strategy will aid in reducing the cost of pneumonia treatment, allowing disadvantaged individuals to receive adequate care at a reduced cost. It will alleviate some of the doctors' workload. This technique will allow doctors to treat more patients for less money, which would benefit everyone.

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