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Detection of Tuberculosis, Pneumonia, Covid-19 using Chest X-Ray

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***Abstract*— Worldwide, infectious illnesses have always posed a serious concern. Millions of people die from illnesses that affect the lungs, such as tuberculosis, pneumonia, and COVID-19. Early screening and diagnosis are necessary to administer appropriate care and stop the disease's spread. A simple, low-cost imaging option is chest X-ray (CXR) imaging. Therefore, the main diagnostic method for all of these chest infections and anomalies is a CXR examination. Paramedics and researchers are working nonstop to create a reliable and accurate method for diagnosing diseases in an effort to save lives. This study aims to classify cases of pneumonia, COVID-19, tuberculosis, and normal using a CXR. The model's goal is to classify the diseases using convolution neural networks (CNN). One kind of deep learning technique that works especially well for computer vision and image recognition applications is the CNN. We will compare and assess the two CNN models in this project: EfficientNetB0 and MobileNetV2 and create an ensemble of these models for an enhanced performance. The dataset that was used in this instance was obtained from Kaggle. The collection has 14,000 images overall, with 3500 images per class and 4 classes (Normal, Tuberculosis, Pneumonia, and COVID-19). This project evaluates how accurate its classification is.**

***Index Terms*— Tuberculosis, Pneumonia, COVID-19, Chest X-Ray, Convolutional Neural Network, Deep Learning, MobileNetV2, EfficientNetB0**

I. INTRODUCTION

Infectious diseases are contagious, they pose a worldwide health risk. There are dangerous infectious infections as well as mild ones. Mycobacterium is the bacteria that causes tuberculosis. A pneumonia infection can be brought on by viruses, bacteria, or fungus. COVID-19 is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV2). All of these ailments affect the lungs. 213 million people are estimated to be affected by these diseases by the World Health Organization (WHO). In light of these findings, it is imperative to concentrate on developing a more thorough knowledge of pulmonary disorders and anomalies. Lately, deep learning has pushed a number of advancements in the healthcare industry. Comparatively, X-ray imaging technology is less expensive and more widely used than Computed Tomography (CT) scans. Tuberculosis, Pneumonia and COVID-19 are examples of infectious diseases that can be clinically identified based on CXR abnormalities and symptoms.

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X-ray images from patients with the aforementioned disorders can be analysed as a definitive way of diagnosis.Consequently, we have developed a deep learning model in this work to proactively identify these diseases to aid radiologists in their decision-making and provide early diagnoses to improve patients' chances of survival or appropriate treatment. The study created a multiclass CNN model specifically made to identify tuberculosis, pneumonia and COVID-19 using CXRs in order to achieve this objective. The research was carried out in four main stages. Initially, the dataset was split, with 64% designated for training, 20% put aside for testing and 16% for validation. After that, the pictures were scaled to 300 x 300 pixel dimensions as part of the standardizing process. During the third stage, the pictures were classified into four different classes using a CNN: Normal, Pneumonia, and Tuberculosis and COVID-19. After that, a thorough assessment of the model's performance was conducted using standards like accuracy, recall, and precision.

II. RELATED WORKS

In order to diagnose lung diseases including tuberculosis, pneumonia, COVID, and normal instances, numerous researches have been conducted in recent years. The following are some of the conducted studies, Vo Trong Quang Huy and Chh-Min Lin [1] presented CBAMWDnet, combined model of Convolutional Block Attention Module (CBAM) and Wide Dense Net (WDnet) is a cutting-edge deep learning network for detecting tuberculosis in CXR images.

Sahar Kazemzadeh, Jin Yu [2] created a deep learning system (DLS) and evaluated its performance against radiologists to identify active pulmonary tuberculosis (TB) on chest radiographs outperforming radiologists. Using cutting-edge machine learning techniques, Linh T. Duong et al. [3] provide a workable approach for COVID-19 detection in lung computed tomography and chest X-ray pictures. Their main classification models are EfficientNet and MixNet, and they use NS, AdvProp, and ImageNet transfer learning methods.

Deep transfer learning is being studied by Irad Mwendo et al.[4] to identify COVID-19, pneumonia, and tuberculosis in CXR images. They evaluate different deep transfer learning methods for automatically predicting COVID-19 pneumonia cases in CXR and CT images, such as MobileNet, DenseNet, Xception, ResNet, InceptionV3, InceptionResNetV2, VGGNet, and NASNet. Tej Bahadur Chandra and Kesari Verma [5] presents an automatic pneumonia detection method using machine learning on segmented lung regions. It emphasizes relevant features within the lung ROI and evaluates the approach with five classifiers including Sequential Minimal Optimization (SMO),

Random Forest, Multilayer Perceptron, Logistic Regression, and Classification by Regression. An effective technique for tuberculosis diagnosis via deep convolutional networks and machine learning was presented by Rajat Mehrrotraa et al. [6]. The model demonstrates potential for COVID-19 and tuberculosis detection, particularly in resource-constrained locations, as it successfully separates tuberculosis-infected images from normal and COVID-infected ones. Deep neural networks (DNNs) trained on simulated pictures were proposed by Lingyi Zhao et al. [7] to recognize COVID-19 features in lung ultrasonography B-mode images, hence removing the requirement for time-consuming manual labeling of in vivo images. Sheikh Rafiul Islam [8] present ChexNet, a Compressed Sensing (CS) based deep learning framework with a 121-layer deep CNN for automated pneumonia detection in CXR images. Xin Zhang et aI [9] introduced CXRNet, an explainable DNN for accurate COVID-19 pneumonia detection in chest radiography images. While conventional deep learning classifiers like AlexNet, DenseNet, and ResNet have shown high accuracy in lung disease classification. Using the chest Computed Tomography (CT) scan images, Shubham Chaudhary et al. [10] established a two-stage CNN based classification system for the detection of COVID19 and Community Acquired Pneumonia (CAP). Mohan bandari et al [11] presents a XAI and CNN models provide clinicians with persuasive conclusions for TB, COVID-19 and Pneumonia detection and categorization. However, its limitation is that the models performance on more extensive datasets remains untested, and exploring advanced data augmentation techniques, like Generative Adversarial Networks, may further enhance its capabilities. Luyao Ma et al [12] developed an AI-based automated tuberculosis detection system enhances diagnostic accuracy using CT images. It uses extra image processing for quality control and a U-Net deep learning system for lesion detection and segmentation. Mohammed Sali Ahmed et al [13] proposed the Multiclass CNN multiclass deep learning model to detect TB, pneumonia, COVID-19 in chest radiographs. The analysis is carried out on a relatively unbalanced dataset, which is a major restriction. As a result, the COVID-19 class has considerably lower accuracy than other classes because it has fewer occurrences than the other classes. Because of this, the study may have been misclassified in some disease categories. Mohammed Sali Ahmed et al [14] put forth a CNN model(Convolution Neural Network Model) and multi-level classification approach that incorporates SMOTE(Synthetic Minority Oversampling Technique) and SVM-SMOTE, oversampling techniques designed to address class distribution imbalances. Mohammed Jamshidhi et al.'s answer [15] uses artificial intelligence (AI) to fight the Covid-19 virus. To achieve this, a few Deep Learning (DL) techniques have been demonstrated, such as Long/Short Term Memory (LSTM), Extreme Learning Machine (ELM), and Generative Adversarial Networks (GANs).

III. METHODOLOGY

A. EfficientNetB0 Architecture:

Convolutional neural network design EfficientNetB0 achieves good performance on image classification tasks with remarkably little model space and computational costs. This effectiveness is achieved using a novel compound scaling technique. The architecture of the model uses bottleneck structures to further increase the network's efficiency and depth-wise separable convolutions to split standard convolutions into distinct depth-wise and pointwise convolutions, thereby lowering computational complexity.Three important model dimensions are carefully balanced by EfficientNetB0 using a compound scaling strategy: resolution (size of input image), depth (number of layers), and breadth (number of channels or filters in each layer).

Through effective scaling of these dimensions, the model could attain cutting-edge precision on image classification benchmarks such as ImageNet, with significantly fewer parameters and lower processing costs as compared to standard designs. EfficientNetB0's technological efficacy makes it a versatile choice for a variety of computer vision applications, offering a strong foundation for task-specific adaptation and transfer learning with a small model footprint.EfficientNetB0 architecture is shown in Fig.1.

B. MobileNetV2 Architecture:

MobileNetV2, a convolutional neural network architecture, was developed mainly for low overhead applications and resource-constrained smartphones.It was released in 2018 and represents a major advancement in deep learning models that are suitable for mobile devices. The core technology of MobileNetV2 is an innovative architecture known as "inverted residuals with linear bottlenecks." Because it applies an expansion layer after applying a bottleneck layer, this model is incredibly efficient for real-time or mobile applications, it reduces the number of parameters and cost of computation by using depth-wise separable convolutions.

MobileNetV2, known for its versatility, allows users to adjust the width multiplier and resolution multiplier in order to balance model size and classification accuracy.

Due to its competitive performance and versatility, it can be used for a variety of computer vision applications, such as object detection and image classification, on devices with minimal processing power. It seeks to optimize the trade-off between efficiency and accuracy in deep learning models from a technology design standpoint.MobileNetV2 architecture is shown in Fig.2.

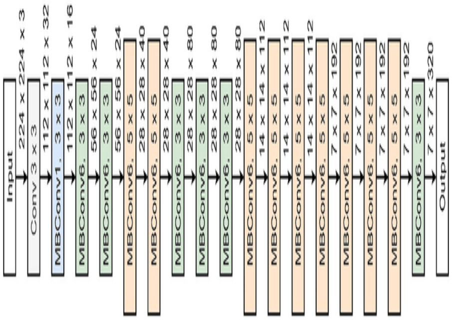

Figure 1.EfficientNetB0 Architecture

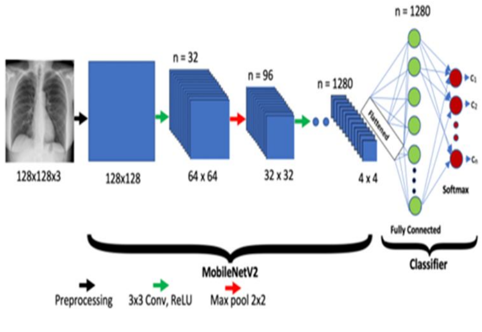

Figure 2.MobileNetV2 Architecture

IV. EXPERIMENTAL STEPS

A. Dataset Description

To perform the study, we have used a dataset that contains images of chest X rays of humans. The dataset contains images that belong to categories namely tuberculosis, pneumonia,Covid-19,Normal represents sample images of each class from the dataset. To improve the dataset's amount and diversity, data augmentation was done. We used this dataset to carry out our study because it was freely accessible and totally available for academic purposes.

B. Sample Dataset

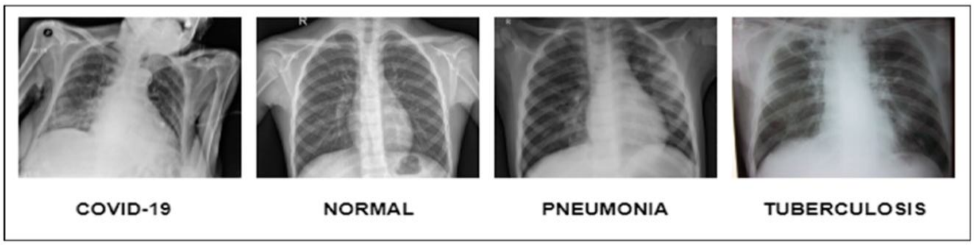

Figure 3.Four classes of dataset

C. Experimental Setup

Additionally, we employ Matplotlib, Pandas, Scikit-Learn and all within the Python programming environment. In our model configuration, we specify 20 training epochs. For optimization, we use the Adam optimizer with a 64-batch batch size and a learning rate of 0.0001. We sequentially employ the EfficientNetB0 and MobileNetV2 architectures for modelling. Subsequently, we merge these architectures to establish our hybrid model.
The data is divided into three categories:training(64%),testing(20%),and validation dataset (16%).Fig.4.A train,test,and validate set is created for each image in the pipeline,so that each image is processed exactly once.

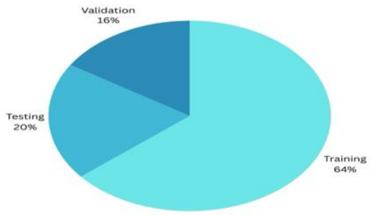

Figure 4. Share of test, train and validation data

D. Data Pre-processing and Data Augmentation

Data pre-processing is achieved by resizing the images to 224 x 224 dimension and made grayscale by applying the conversion method. Then the images are normalized form (0,255) to (0,1). COVID-19 and Normal/unaffected. The dataset has been obtained from Kaggle. The dataset contains 1000 images from each category making it to 4000 in total. Fig.5.
We rely on data augmentation to generate a balanced dataset and enhance the deep learning models' performance for limited datasets. Upon data augmentation, the images that were initially 1000 in each category increased to around 3500 in each category making it around 13500 in total. Four image augmentation methods—rotation, flipping, shearing, shifting— are used to produce the images. For image augmentation, we rotate the images clockwise and counter clockwise by no more than of 5 degrees. Shearing is performed at 0.2%, we shift the images 20% by height and 20% by width and flipping is performed both horizontally and vertically. Fig.5. represents sample images after augmentation.

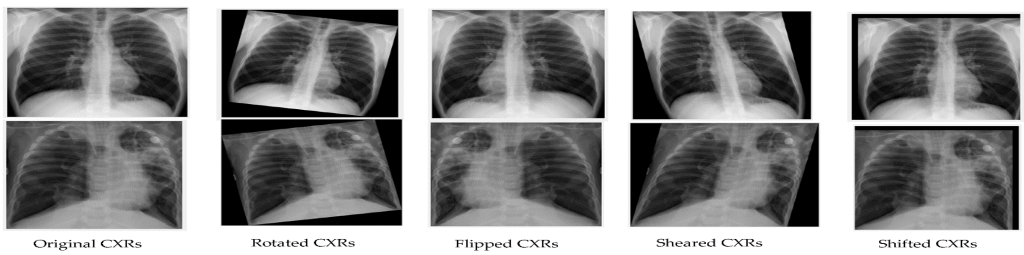

Figure 5. Sample Augmented Images

E. Pretrained deep learning models

We have employed the two most standard models EffectiveNetB0 and MobileNetV2. Its unique width and depth scaling, which effectively modifies the filter size in each layer, is what makes the EfficientNetB0 unique. A 3x3 convolutional layer serves as the first feature extraction layer. and subsequent blocks employ a mix of 1x1 and 3x3 convolutions, changing the filter's size based on the layer's depth. In particular, 3x3 convolutions are often used in the early layers, when the features are often finer-grained and more localized. These tiers gather certain information inside more compact response areas. As the network gets deeper, 1x1 convolutions are added to lower the number of channels and processing overhead. This optimal effective capture of both local and global properties is made possible by the adaptive filter size technique. In comparison to computational cost, the findings are more accurate due to the efficient use of parameters and computing. The accuracy, loss and precision achieved by this model across different epochs is shown in Fig.6.

```
146/146 [==============================] - 512s 4s/step - loss: 0.1085 - accuracy: 0.9803 -
precision: 0.9631 - recall: 0.9578 - val_loss: 0.2788 - val_accuracy: 0.9510 - val_precision:
0.9070 - val_recall: 0.8960 - lr: 0.0010
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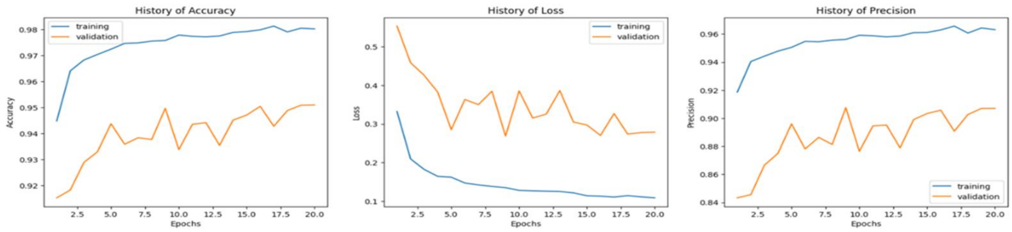

Fig.6. Accuracy, Loss and Precision of EfficientNetB0 Model

MobileNetV2, designed for efficient and portable deep learning applications, optimizes its performance using certain building blocks and filter sizes. MobileNetV2 primarily uses 3x3 depth wise separable convolutions, which separate spatial and channel-wise convolutions. It adds inverted residual blocks using 1x1 and 3x3 convolutions for feature extraction.Additionally, MobileNetV2 makes use of skip connections, often called shortcut connections, to improve training and gradient flow. These connections allow the network to understand and detect both superficial and deep features. The accuracy, loss, precision achieved by this model across different epochs is shown in Fig.7.

```
146/146 [==============================] - 535s 4s/step - loss: 0.0823 - accuracy: 0.9851 -
precision: 0.9723 - recall: 0.9681 - val_loss: 0.3871 - val_accuracy: 0.9432 - val_precision:
0.8919 - val_recall: 0.8792 - lr: 0.0010
```

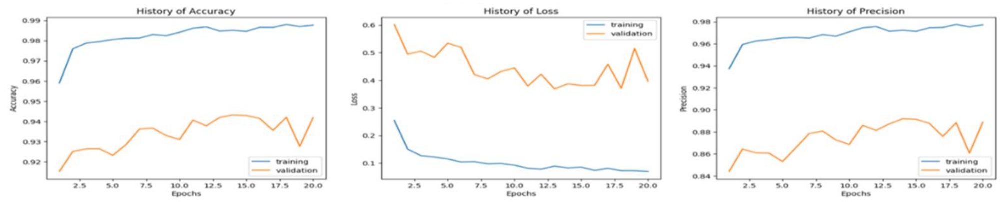

Fig.7. Accuracy, Loss and Precision of MobileNetV2 Model

F. Transfer Learning

Transfer learning has made it possible to train deep neural networks even with a small amount of input by utilizing the capacity to apply previously developed models and their expertise to new contexts. Through transfer learning, the expertise of a machine learning model that has already been trained is applied to a different but related problem. Better performance, reduced training time, and a reduced data requirement are just a few advantages of this. Feature extraction layers are the foundational levels of the pretrained model that are usually left intact. These layers have learned to recognize basic patterns and features in data, like edges and textures. We don't change these layers because they capture general, useful information that can help with many tasks. We frequently swap out the pretrained model's last few layers, which is called the output layer with a new output layer that's tailored to our target task. In between the feature extraction layers and the output layer, there are intermediate layers that capture more complex patterns. We might fine-tune some of these intermediate layers to make the pre- trained model better suited for our specific task. This process helps the model learn the right details for the new task while preserving the useful features it already knows.

For our study we have removed the final layers of the pretrained models, both EfficientNetB0 and MobileNetV2 and added two fully connected layers.

Initially, to prevent overfitting, first a 0.5 rate dropout layer is applied, then multidimensional maps are converted to one dimension by flattening, batch normalization assures stable training. Following the introduction of the first fully connected layer, which has a dimension of 32, batch normalization and relu activation are carried out once more. Finally, another fully connected layer with dimension of 4 is introduced with SoftMax activation to perform multi class classification. This completes the individual models separately. The representation of the models is shown below in figure 8.
Then both the trained models are used to train the hybrid model called as ensemble model. The architecture of the ensemble model is depicted in figure 9.

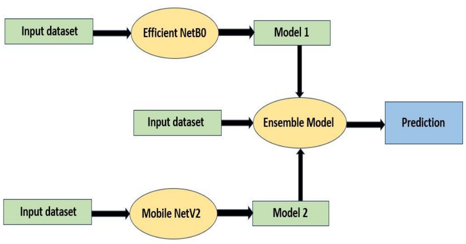

Figure 8. Ensemble Model

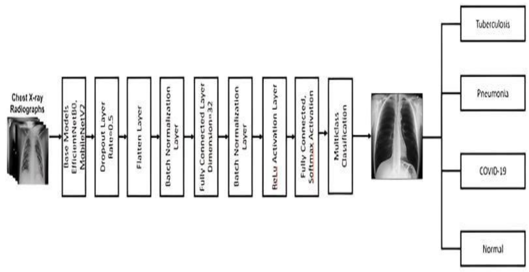

Figure 9. Architecture of Ensemble Model

G. Classification

Our model performs Multiclass classification i.e. categorize our input into one of 3 or more classes. Multiclass classification involving 4 classes is the output of our models (Tuberculosis, Pneumonia, COVID-19, Normal). It predicts the input given into one of the above classes.

V. PARAMETER FOR EVALUATION

A. Accuracy

Accuracy is the amount of correct classifications a trained machine learning model makes. Based on the scale used, it is expressed as a value between [0,1] and [0,100]. If the classifier's accuracy is 0, it consistently guesses the incorrect label and if it is 1, or 100, it consistently predicts the right label. Accuracy is defined as the ratio of correct to total predictions. Correct predictions are comprised of True Positives (TP) and True Negatives (TN), while all predictions are made up of all positive (P) and negative (N) cases. Equation (1) provides the accuracy calculation formula.

$$Accuracy = \frac{(TP + TN)}{(P + N)} \quad (1)$$

For tasks involving balanced classification, accuracy is a useful statistic. It is a crucial statistic since it is a very straightforward indicator of model performance.

B. Precision

The definition of precision is the ratio of correctly identified positive samples (TP) to the total number of correctly or wrongly categorized positive samples (TP + FP). It indicates us how many of the positive cases are correctly identified by the model. Equation (2) indicates the formula to calculate precision.

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

In areas like fraud detection or medical diagnosis, where the cost of false positives is significant, precision is crucial. For the model to be reliable and useful in these situations, a low rate of false positives must be maintained. So, precision is a crucial factor in the field of machine learning since it helps with both the accuracy of positive forecasts and decision-making in real-world applications.

C. Recall

The proportion of Positive samples that were accurately identified as Positive (TP) relative to all Positive samples (TP + FN) is known as the recall. Equation (3) provides the recall calculation formula.

$$Recall = \frac{TP}{(TP + FN)} \quad (3)$$

Recall, in contrast to Precision, is unaffected by the quantity of incorrect sample classifications. Additionally, If the model classifies all positive data as positive, then recall will be 1.Recall, also known as sensitivity or true positive rate, is an important metric in deep learning, especially for applications where it can be detrimental to miss positive cases. A high recall shows that the model is successful in identifying a sizable percentage of the positive cases in the dataset. This measure guarantees that the model has a low likelihood of failing to detect true positive occurrences, which makes it important in many real-world applications.

VI. Results And Discussion

On the training and validation data, we train MobileNetV2, EfficientNetB0, and Ensemble model using multi-class classification, with class 0 representing Normal, class 1 indicating COVID-19, class 2 representing Pneumonia, and class 3 representing Tuberculosis.

A graph representing the accuracy and loss function for each model is shown versus the number of epochs using training and validation data. The MobileNetV2 model exhibits instability as well, with a striking discrepancy between the outputs of the training and validation data. The training data's accuracy of 98.51% and loss of 0.08% show how well it can catch complicated features. 94.32% of the validation data is correct, and the validation loss is 0.38%. The graphs of accuracy, loss and precision for this model is depicted in figure 4.5.4, 4.5.5 and 4.5.6 respectively. The EfficientNetB0 model's training accuracy is 98.03%, and its loss is 0.10%, demonstrating the model's ability to minimize errors. 95.10% is the validation accuracy, while the validation loss is 0.27%. The graphs of accuracy, loss and precision for this model is depicted in figure 14,15 and respectively. It is more accurate than MobileNetV2 Model. For the Ensemble model training data’s accuracy is 98.92%, and the loss is 0.07. Validation data's correctness is 95.77%, and validation loss is 0.24. The graphs of accuracy, loss and precision for this model is depicted in Figure.10.This amalgamation leverages the unique capabilities of the individual models, delivering superior accuracy. EfficientNetB0 showcases remarkable accuracy and stability, outperforming MobileNetV2. The Ensemble model, benefiting from the combination of strengths, attains superior accuracy, ultimately demonstrating the potential and significance of leveraging ensemble techniques in complex multi-class classification tasks. Also the ensemble model outperforms the other models when trained for 5,10 and 20 epochs. Performance of ensemble model at different epochs have been depicted in Table I. Comparison Results are shown in Table II,Fig.11,Fig.12.

```
146/146 [==============================] -3968s 27s/step - loss:0.0759 - accuracy: 0.9892 - precision: 0.9812 - recall: 0.9754 val_loss:0.2456-val_accuracy:0.9577-val_precision:0.9231-val_recall: 0.9064 - lr: 0.0010
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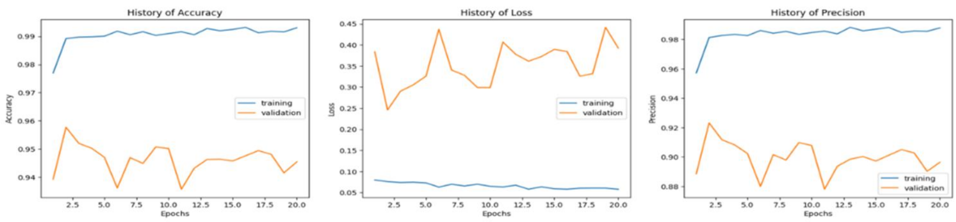

Fig.10. Accuracy, Loss and Precision of Ensemble Model

TABLE I. PERFORMANCE OF ENSEMBLE MODEL AT DIFFERENT EPOCHS

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Precision	Recall
5	0.9900	0.0729	0.9470	0.3258	0.9022	0.8840
10	0.9806	0.1148	0.9231	0.5344	0.9077	0.8913
20	0.9877	0.0696	0.9419	0.3964	0.8963	0.8840

TABLE II. COMPARISON OF MODELS

	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Precision	Recall
MobileNetV2	0.9851	0.0823	0.9432	0.3871	0.8919	0.8792
EfficientNetB0	0.9803	0.1085	0.9510	0.2788	0.9070	0.8960
Ensemble	0.9892	0.0759	0.9577	0.2456	0.9231	0.9064

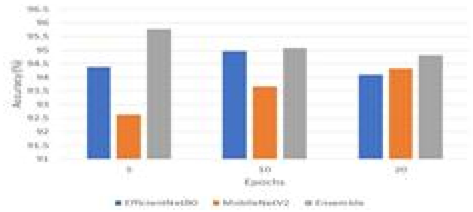

Figure 11.Comparison of Models at different epochs

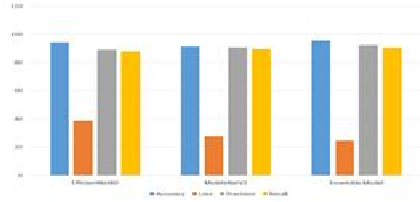

Figure 12.Comparison of Parameters of Models

VII. CONCLUSION AND FUTURE ENHANCEMENTS

As a result, our ensemble model, which is a hybrid model, provides greater accuracy, precision and recall than EfficientNetB0, MobileNetV2 models individually. In order to accurately diagnose COVID-19, pneumonia, tuberculosis, and normal diseases in chest X-rays, we investigate the vital area of deep learning. Early disease diagnosis plays a major role in healthcare in improving patient's condition, stop the spread, and boost the effectiveness of medical treatment. Our study, which makes use of the priceless data from chest X-rays, stresses the significance of a balanced dataset for assuring accurate and impartial disease classification. Pre-trained models can be made more generic and better at categorizing medical images by using data augmentation approaches and transfer learning. Moreover the addition of ensemble model improves the overall resilience and accuracy of categorization. Looking ahead, the ability to anticipate numerous diseases at once is an interesting breakthrough with significant implications. This research endeavours to contribute to the ever-evolving landscape of medical image analysis, ultimately helping in diagnosis of diseases timely and accurately.

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