An Efficient Transfer Learning-Based Framework for Health Care Application

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Abstract – Deep learning has revolutionized healthcare applications, particularly in the diagnosis, treatment, and management of infectious diseases. The main objectives of this investigation are to propose several methods for assessing high-resolution X-ray images with the purpose of identifying the occurrence or not of symptoms associated with pneumonia. The objective of this exam was to identify fixes for these existing problems. Our offering entails a deep learning (DL) technique for detecting chest anomalies using the X-ray modality using the EfficientNet B0 model. In order to make accurate diagnoses of pneumonia, both the EfficientNet B0 and the upgraded CNN model undergo extensive data-driven training. The CNN model that underwent upgrades was determined to be the most effective in this analysis because to its high level of accuracy. The results of our research conclusion are that DL models are capable of monitoring pneumonia's development, increasing diagnostic precision overall and giving patients new optimism for immediate relief.

Keywords – Deep Learning, EfficientNet, Classification, X-ray, Pneumonia.

I. INTRODUCTION

Deep learning has made recent movements, and many medical image processing opportunities now show promising results. Chest radiographs [1] are a special technique for which several potential uses have been investigated since they are the most often conducted radiological test. Chest radiography, also known as CXR, has been a long-standing and frequently used imaging technology for many years.

The radiologist's expertise and the caliber of the X-ray imaging are used to formulate high-precision X-ray conclusions. Many treatments are only helpful for the majority of illnesses in their early, symptomless stages. Finding precise lung borders and classifying them as normal or abnormal (with diseases) are crucial stages in the automated interpretation of CXR images. It is a frequently used technique for early diagnosis in clinical settings to monitor heart-related defects, such as lung and heart disease, hemorrhage, consolidation, pneumothorax, pleural effusion, swelling, and inflation [2]. In some diagnostic situations, data based on closely related images of lung boundaries can be extracted without further analysis.

Each year, pneumonia causes more than 1 million hospital admissions and approximately 500,000 fatalities in the United States alone [3]. In accumulation to this, the WHO revealed in 2019 that pneumonia claimed the lives of 14% of children under the age of 5 globally. This encourages the development of a DL-based model for early pneumonia prediction in order to preserve valuable human lives by administering prompt treatment and lowering the elevated mortality rate brought on by pneumonia. Chest X-ray (CXR) pictures are a significant tool in epidemiological research and medical treatment for identifying pneumonia since they are both highly effective and widely available. The process of identifying pneumonia in CXR pictures is complex and demanding, necessitating the presence of qualified radiologists.

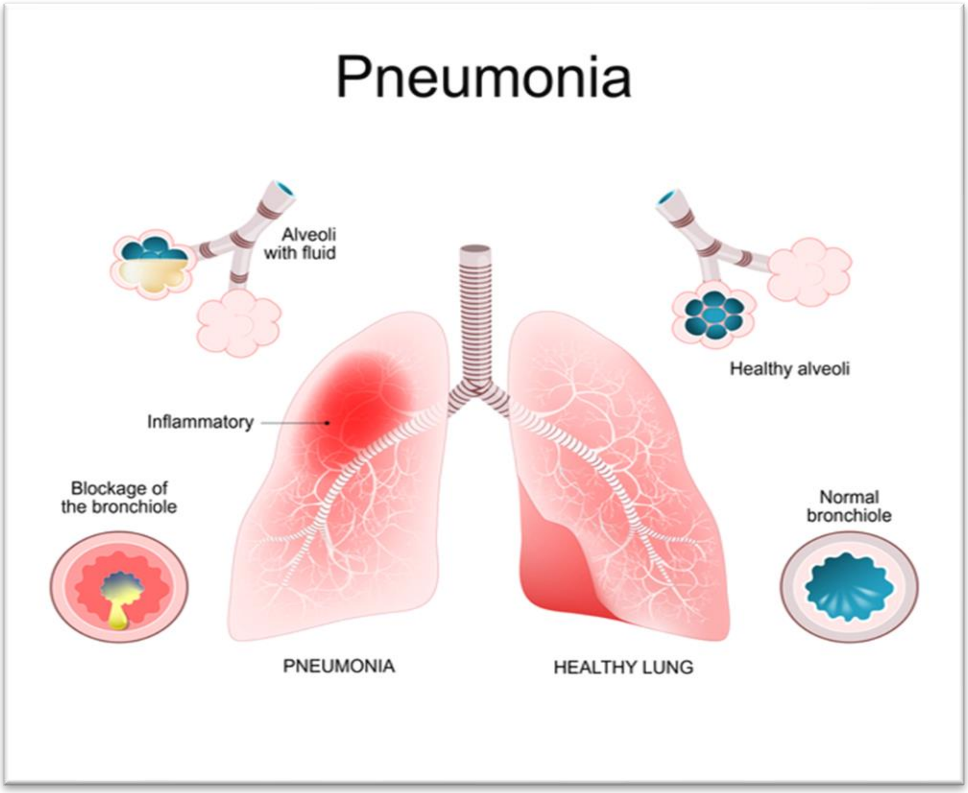


Fig 1. (a) Normal (b) Pneumonia cases.

Considering that CT scanners can evaluate three-dimensional data, several researchers have concentrated on utilizing them to diagnose pneumonia. However, the use of CT scanners as a method for diagnosing pneumonia is a costly one. There must be a less expensive and quicker way to handle the enormous number of people waiting for a test for a system to be useful during a pandemic. Benefits of chest X-rays for this application include mobility, single-surface cleaning, fast diagnostic measures, and lower treatment costs. The benefits of X-ray technology make it feasible for researchers to investigate its usage in pneumonia diagnostics [4]. **Fig 1** displays examples of chest images illustrating distinct features between normal cases and instances of pneumonia.

Recently, AI solutions [5] for health challenges including skin, brain, and breast cancer detection have been developed utilizing handcrafted, deep learning, and machine learning methodologies. In truth, DL is a branch of machine learning as well as AI that applies complex artificial neural networks to provide the most recent advancements in a variety of fields, including recognizing voices, translators of languages, and several.

Classifying different CXR illnesses properly and on time may be difficult because to the numerous similarities between distinct chest ailments [6]. Further complicating the classification procedure are the input samples' frequent distortion, fading, light variation, and brightness changes. To discover and classify the 8 distinct types of chest anomalies, The X-ray imaging modality and the EfficientNet model were both used in the creation of a brand-new framework that has been given the name "Chest Abnormalities' Detection." This paradigm tries to solve the shortcomings of earlier techniques by addressing those constraints head-on.

The objective of this effort was to create a DL framework will categorize the results into two distinct groups: regular instances and pneumonia cases.

The testing results show that our technology is capable of identifying between the various types of chest illnesses even when there are various imagine abnormalities. The following are the planned work's main contributions:

- The increased recognition capability of the proposed framework to handle complicated sample transformation changes improved classification performance. The CXray-EffDet methodology, with its one-stage object identifier, offers a computationally efficient method for categorizing chest illnesses from X-ray data.
- The research investigation that is being proposed can identify both the locations of ill regions and the class that is connected with those places.
- To demonstrate the reliability of our approach, we provide a comprehensive analysis of the most recent techniques for the classification disorders then carry out tests on a complex data known as the Chest X-Ray Images dataset.

This paper's organization continues below. Section 2 shows recent relevant work evaluations. Presenting DL algorithm backdrop In Section 3, we provide our suggested framework for pneumonia. The technique and experimental findings from our suggested models are detailed in Section 4. Final results and future work are in Section 5.

II. RELATED WORK

Chest X-rays may be used in a number of different ways to assist diagnose pneumonia, which has led to the change of a numeral of different diagnostic approaches. Many of these approaches use a mixture of human feature extraction techniques and a machine learning algorithm to make classifications. Conversely, several approaches employ deep learning algorithms to both perform identification and classification of features [7]. By modifying the features of deep layered CNNs, these methods have made it possible to identify pneumonia with a high degree of accuracy.

Ho et al.'s [8] two-phase strategy was suggested for correctly classifying 14 different chest illnesses from X-ray data. Utilizing activation weights from a pre-trained DenseNet121 network's last convolutional layer, they first identified abnormal locations. In the subsequent step of classification, key point fusion was accomplished by fusing patterns and deep characteristics. SVM, KNN, and AdaBoost were just a few of the supervised learning algorithms used to classify composite attributes. The tests showed that the ELM (Extreme Learning Machine) predictor fared better than other students, with an accuracy of 84.62% in this difficult job of identifying chest disorders. The automated COVID-19 screening model that Singh et al. [9] proposed 30 is put into practice by combining deep transfer learning frameworks.

The creation of an innovative diagnosis platform that utilizes the categorization and examination of chest X-rays [10]. Higher forecasting precision is attained by using an explainable method and convey how training-learning models behave. The implied technique's average accuracy is over 96%, making it a viable alternative to human reading for massive amounts quick COVID-19 screening. The concept of confidence-aware anomaly identification was first presented by Zhang et al. [11] for CXR images. The strategy consisted of extracting features from a backbone network that was constructed using ResNet18. These characteristics were used for classification using a contrastive loss to maximize the detection between anomaly and non-anomalous instances and a confidence prediction network to rectify any errors that may have been generated.

Y.-G. Kim et al [12] presents a novel automated framework that makes use of DL-based method to segment 4 areas of the lung. The primary work an ensemble technique that makes use of five different models has been developed in order to improve the segmentation process. This has led to an increase in both the accuracy and the resilience of the detection of lung opacities.

I. M. Baltruschat et al [13] aimed to assess the efficacy of two sophisticated picture pre-processing approaches enhancing the performance of DL methodologies. This study investigates the enhancing the efficient of a CNN. The author put out an innovative ensemble architecture that aims to harness the synergistic information included in diverse images, drawing an analogy to the workflow of a radiologist. The necessity for more research to advance the clinical application and incorporate illness segmentation for multi-label classification has been recognized.

J. Stubblefield et al [14] a deep-learning model was created and trained using an external picture dataset in order to extract visual characteristics and enhance the classification accuracy of a dataset that had a limited amount of image data. This study emphasizes the significance of clinical characteristics in the categorization of patients in the emergency room, specifically focusing on the differentiation between cardiac and infectious etiologies. The review conducted by the model of the imaging features associated with cardiac and infectious causes is consistent with existing medical knowledge. This analysis offers valuable insights into the predictive variables specific to each category. The outcomes of this work provide a significant contribution to the progress of a machine learning model that might assist emergency department physicians in accurately detecting cases of acute dyspnea, hence reducing the unnecessary prescription of antibiotics. The research moreover discusses the potential utilization of DL methodologies in the automated identification and assessment of diverse medical conditions, including lung cancer, breast cancer, and skin cancer.

In this study, Almezhghwi et al. [15] provide the examination and categorization of chest X-ray images, aiming to detect and diagnose various chest ailments. The suggested methodologies employ SVMs that have been trained using the AlexNet and VGGNet16 deep learning models. The authors offer unique DL approaches for quick and automatic classification of chest X-ray images. The approaches that have been proposed exhibit superior performance compared to the DL approaches of AlexNet and VGG16 in the context of classifying input dataset.

T. Agrawal and P. Choudhary [16] the utilization of GAN models in the segmentation and classification of chest X-rays has garnered attention within the computer vision field. This interest stems from the models' capacity to tackle the paucity of medical data. To the best of our knowledge, this is the first review to explore these aspects collectively. This paper provides a study of DL X-ray interpretation among radiologists and physicians. This discourse pertains to the difficulties associated with the acquisition and annotation of extensive image datasets, as well as the resultant computational strain imposed on DL models.

S. Phine [17] applied using pre-trained models like VGG19, VGG16, and Xception for more accurate detection outputs. This research also emphasizes the use of ML methodologies. In the categorization of individuals diagnosed with pneumonia. This classification is performed by analyzing features derived from chest X-ray pictures.

III. METHODOLOGY

This research presents a potential optimal algorithm for the identification of pneumonia using Chest X-rays. Data augmentation techniques were implemented in order to expand the amount of the dataset, which was initially limited in scope. The architecture of the pre-trained EfficientNet B0 model has been fine-tuned specifically for the job of classifying pneumonia.

The process of scaling up the EfficientNet B0 model architecture is accomplished by the employment of compound scaling, as defined in the work by Tan et al. (2019) [18]. The succeeding sections elaborate on the several strategies employed in the suggested methodology.

Convolutional Neural Network

The inception of CNN was marked by its implementation with T. Agrawal and P. Choudhary [16]. However, the field of computer vision experienced a significant breakthrough with the emergence of AlexNet, which revolutionized the field following its victory. In subsequent years, other architectural modifications have been proposed for the purpose of enhancing classification performance on the ImageNet dataset. Notably, the AlexNet variations have emerged as particularly effective in achieving this objective. In the ILSVRC-12 competition, the AlexNet model attained a top-5 accuracy of 84.7%. Similarly, in the ILSVRC-17 competition, the NASNet model earned a remarkable top-5 accuracy of 96.2%. This subsection provides a concise analysis of prevalent deep Convolutional Neural Network (CNN) designs.

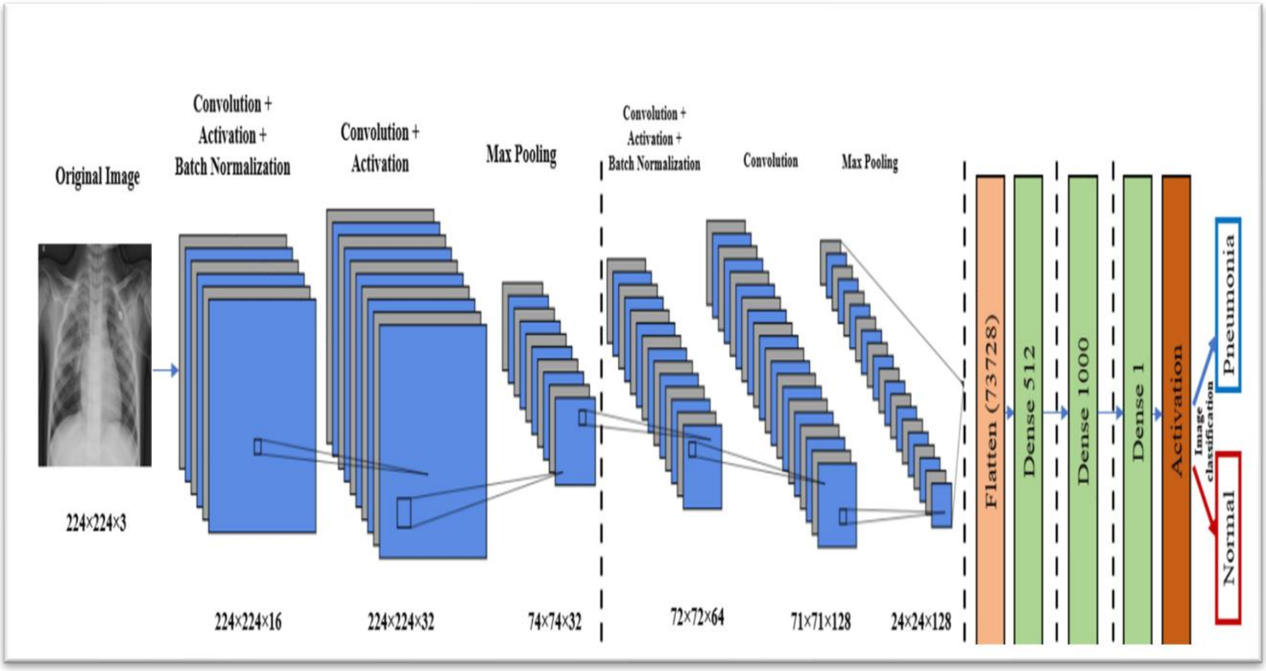


Fig 2. CNN Architecture.

Four separate convolutional neural network the component responsible for feature extraction. Each individual block in this architecture is made up of a convolutional layer. These three layers make up the bulk of each block. Those layers are both components of the architecture that is shown in **Fig 2**. The findings that were acquired from the step of feature extraction are then put into the flattened layer so that the data structure can be transformed. This structure is fit for the dense layer of classification, which will ensure that space is used effectively.

A type of layer seen in neural networks known as the dense layer is distinguished by the numerous and regular interconnections that it has between its constituent neurons.

Transfer Learning

CNNs typically need bigger datasets for effective training. When CNNs are trained using fewer datasets, their ability to generalize is diminished. The utilization of transfer learning can be employed in such instances. **Fig 3** illustrates the concept of transfer learning, wherein a model acquires knowledge while solving a specific issue and subsequently applies this knowledge to solve another problem. The process of retrieving data from an image using computational methods might be referred to as image processing. The process of analyzing an image by identifying and separating its constituent objects or regions is referred to as image segmentation. Object detection is a useful technique for distinguishing between different items, however it does not provide assistance in accurately identifying the boundaries of said objects. The square box is applied in order to enclose the object for the purpose of identification. The accurate and automatic segmentation of chest X-rays presents a hard task due to the variability in lung size, the presence of rib cage borders, and the clavicle. The process of segmentation in chest X-rays is conducted to achieve the segregation and separation of the lungs, heart, and clavicles. The researchers employed a transfer learning approach to refine the performance of a pre-trained model by utilizing a lung segmentation dataset. The pre-existing models underwent a process of fine-tuning.

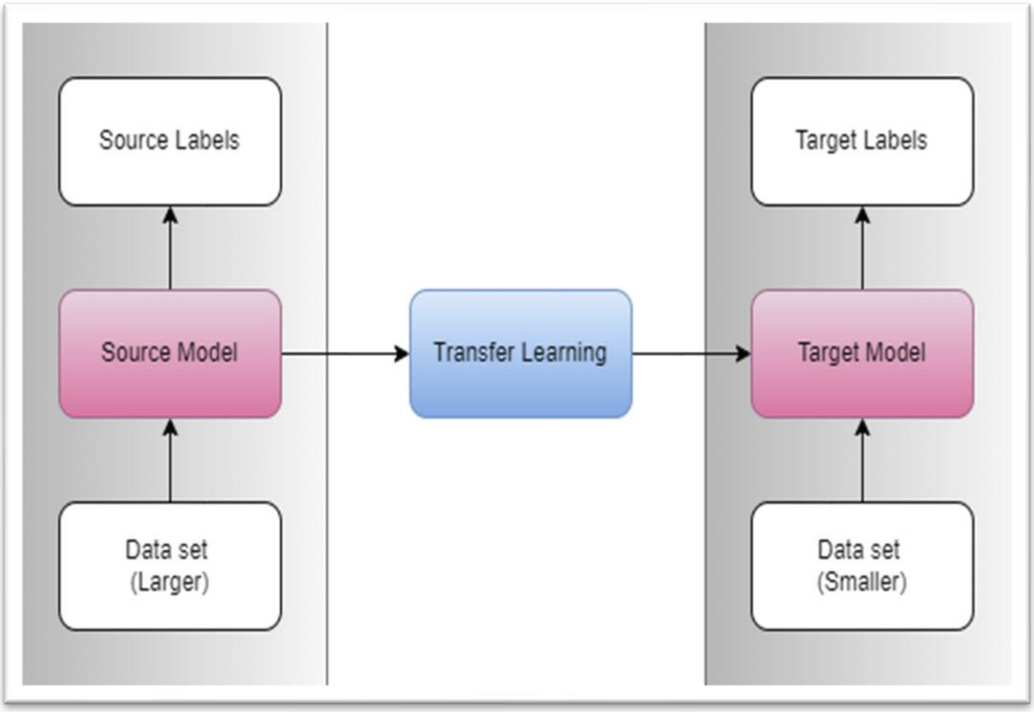


Fig 3. Overview of Transfer Learning.

Data Augmentation

Data augmentation is a technique employed during the training phase to increase the size of the training dataset. Data augmentation can be utilized for image change during training. Using data augmentation approaches, we may progress the model's outcome by fixing the issues of overfitting, which in turn greatly improves our capacity for inductive reasoning. The CNN approach possesses some characteristics, such as partial translation-invariance, and the utilization of augmentation procedures, including the inclusion of translated images, which can significantly improve its generality abilities. There is a vast range of options available when it comes to data augmentation strategies, by interpreting photos in different ways to emphasize crucial qualities. In making this determination, the following criteria have been taken into account: During the period in which we are learning, we make use of several augmentation methods, such as horizontal flip, rotation, shear, and zoom.

$$\mathrm{E} = mc^2 \tag{1}$$

Segmentation

The process of retrieving data from an image using computational methods might be referred to as image processing. The process of analyzing an image by identifying and separating its constituent objects or regions is referred to as image segmentation. Object detection is a useful technique for distinguishing between different items, however it does not provide assistance in accurately identifying the boundaries of said objects. The square box is applied in order to enclose the object for the purpose of identification. The accurate and automatic segmentation of chest X-rays presents a hard task due to the variability in lung size, the presence of rib cage borders, and the clavicle. The pre-existing models underwent a process of fine-tuning.

EfficientNet

The researchers employed a transfer learning approach to refine the performance of a pre-trained model by utilizing a lung segmentation dataset. The pre-existing models underwent a process of fine-tuning. The EfficientNet architecture is a convolutional neural network model that has gained significant attention and popularity in the field of computer vision. The models employed in this study are founded upon straightforward and remarkably efficient compound scaling techniques. This approach allows for the expansion of a foundational Convolutional Neural Network (ConvNet) to accommodate various resource limitations, while yet preserving the efficiency of the model. It is commonly employed in datasets for transfer learning. EfficientNet models, in general, demonstrate superior accuracy and efficiency compared to established CNNs such as AlexNet, ImageNet, GoogleNet, and MobileNetV2. EfficientNet has the potential to serve as a novel basis for forthcoming computer vision endeavors. Up to this point in time, the researchers are aware of no work that has been done employing EfficientNet for the purpose of transfer learning in the context of the COVID-19 classification.

EfficientNet is preferred above other one-stage detection algorithms due to its ability to achieve lowest completion time for the classification task, without compromising prediction performance. While two-stage detection models exhibit enhanced accuracy in identifying medical anomalies, this advancement is accompanied by a significant increase in computational complexity. This is due to the necessity of conducting two distinct stages to locate and classify regions of interest (ROIs), rendering these methods unsuitable for practical applications. The concluding phase of the proposed study focuses on the identification and classification of the detected segment into eight distinct categories of chest ailments. **Table 1** provides a comprehensive explanation of the training parameters that were used during model training.

Table 1. Hyperparameters of EfficientNet

Parameters	Values
epochs	25
Learning rate	0.001
Batch size	16
confidence	0.5
unmatched	0.5

EffNet's first step is to run the image through the EfficientNet-B0 features extractor, which then generates a large set of test features. The system performs both feature extraction, iteratively combining multiple feature maps to calculate the final set values. During the last stage, the sick region that has been discovered is presented alongside its corresponding projected class label. The work of the model is then measured using assessment parameters commonly employed in computer-aided medical image processing. **Fig 4** shows the proposed model architecture.

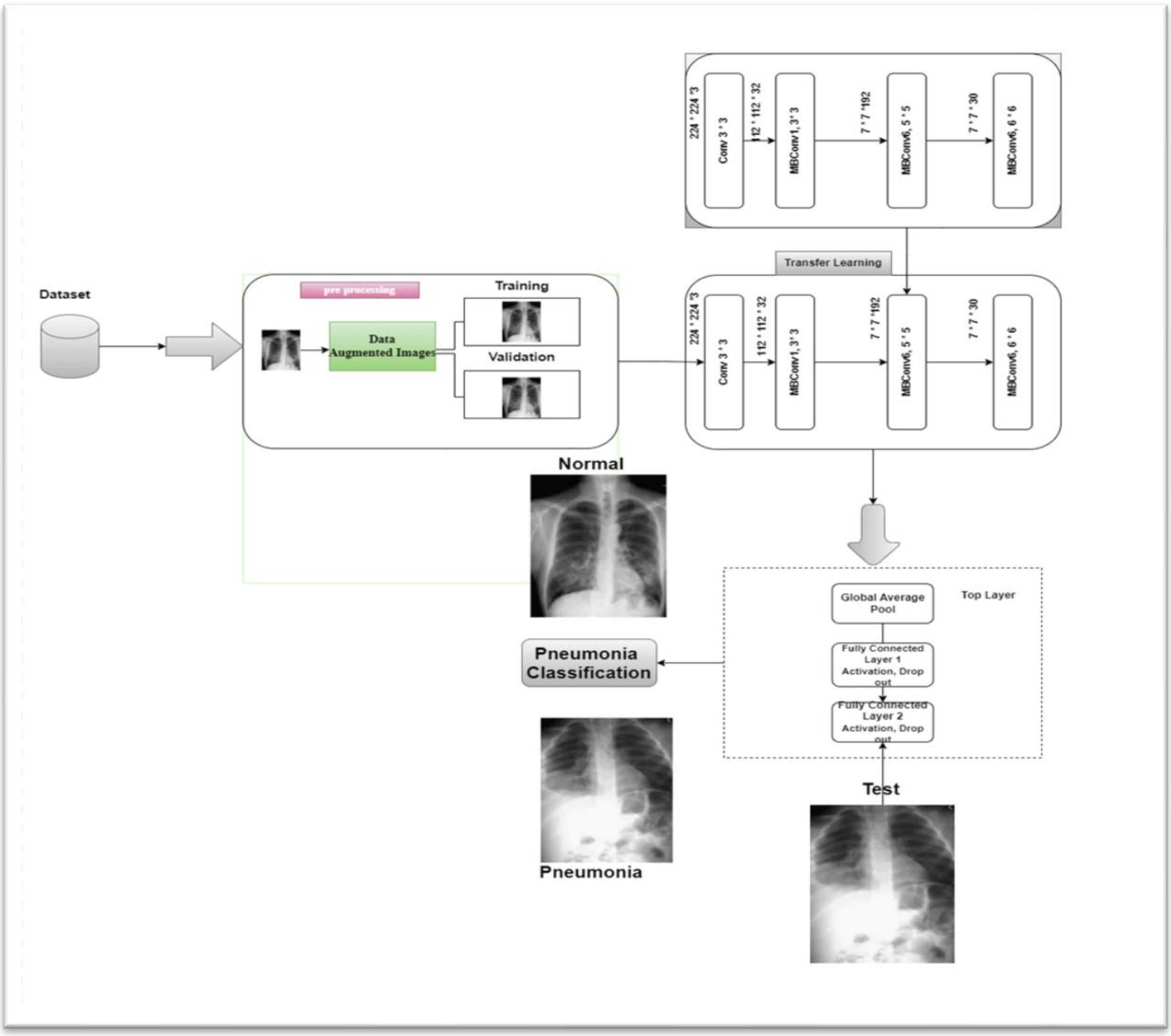


Fig 4. Proposed Model using EfficientNetB0 Architecture.

The initial step in the EffNet technique involves utilizing the EfficientNet-B0 features extractor and calculates a comprehensive collection of sample features. During the last stage, the sick region that has been discovered is presented alongside its corresponding projected class label. **Fig 5** shows the scaling function in EfficientNet architecture.

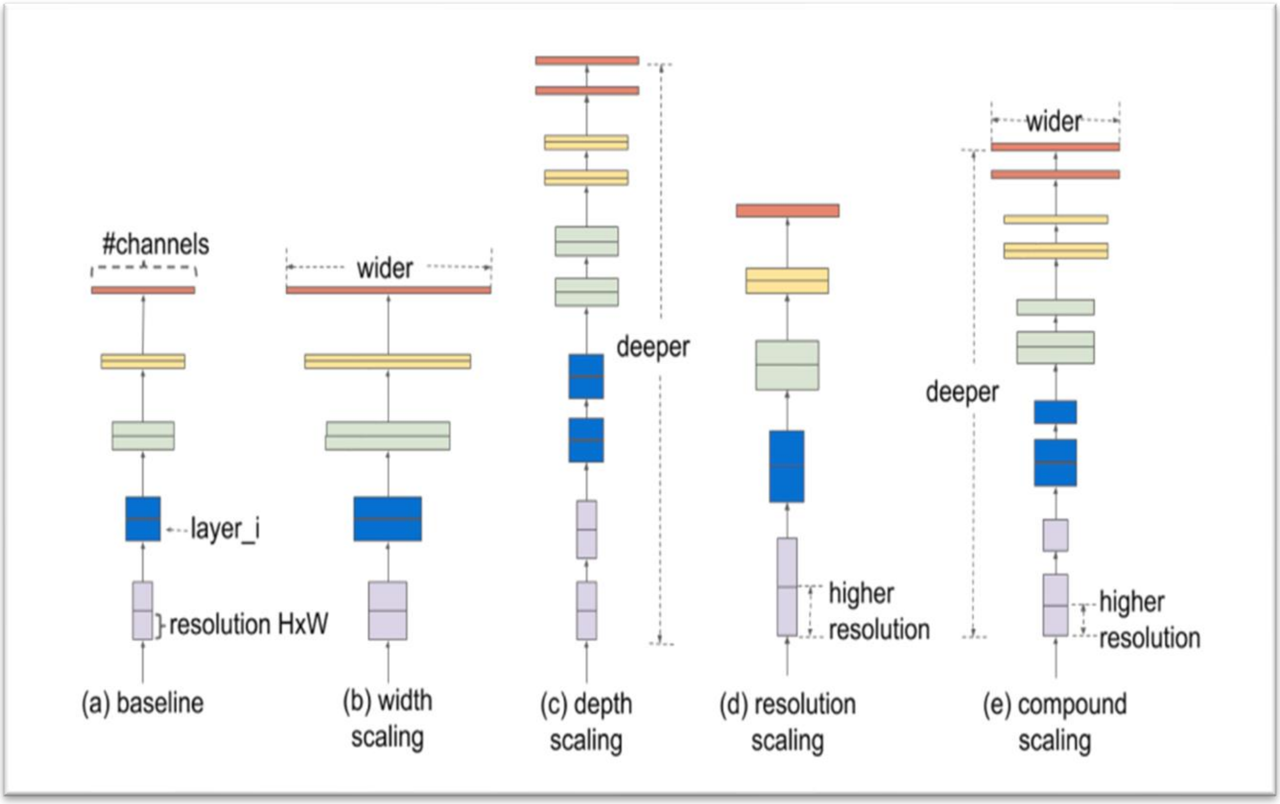


Fig 5. Scaling Function in EfficientNet Architecture [19].

The ultimate result that is subsequently surveyed by a system. In order to carry out the outcome task commonly referred to as a fully connected (FC) layer, was employed. Within the architecture of our model, we incorporated batch normalization, activation, and dropout layers between the FC layers. The utilization of this technique enhances the efficiency of the optimization process, leading to a more foreseeable and consistent gradient performance, thereby expediting the training procedure. In the present study, when selecting an activation function, the preference was given to Swish, which is formally described as

$$f\ (x)\ = x \cdot \sigma\ (\ x\ ) \tag{2}$$

$$\sigma(\ x\ ) = (1 + \exp(-x\ ))^{-1} \tag{3}$$

Consider their respective properties and performance characteristics. The Swish activation function regularly demonstrates superior performance and when applied to deep networks in many demanding domains. The Swish function exhibits several key qualities that contribute significantly to its enhancement. After completing the activation step, we included a Dropout layer, a well-known regularization approach that is used to address overfitting and improve the accuracy of predictions. The aforementioned layer has the capability to randomly eliminate specific nodes within the FC layer.

The number of nodes that are picked and rejected. The value of p can be ascertained by two methods: employing a employing a random estimate, such as assigning p a value of 0.5. Throughout this training, dropout value is 0.3. These class scores were then utilized to ascertain the input, which could be categorized as normal, or pneumonia. In mathematical terms, the softmax activation function may be described as follows:

$$s(y_i) = \frac{e^{y_i}}{\sum_{j=1}^{C} e^{y_j}} \tag{4}$$

$$l = -\sum_{n=1}^{N} \log\left(\frac{e^{y_{i,n}}}{\sum_{j=1}^{C} e^{y_{j,n}}}\right) \tag{5}$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The installation of deep learning frameworks for pneumonia diagnosis was conducted using the Python programming language and Keras. The training and validation steps utilized the GPU runtime in Google Colab.

Dataset

The original data set from the Guangzhou Women and Children's Medical Centre [20] consisted of a total of 5836 photographs. The dataset included of photos depicting both individuals with healthy lungs and individuals diagnosed with pneumonia. A total of 1583 chest X-ray scans were found to be free from any pathological abnormalities. The dataset was partitioned into two sets, namely the training set and the test set. The test set consisted of 700 photos, while the training set had 5136 images.

Evaluation

The model was initially trained with the data from the provided training set, and it was subsequently validated with the information from the provided validation set [21]. On the other hand, the test set was utilized to evaluate the efficacy and generalization capabilities of the model. The dataset contained information that was not included during the training process.

Consequently, multiple metrics were employed on the testing set to evaluate the efficacy of the suggested methodology. These metrics encompassed sensitivity (Sens) or recall (Reca), specificity (Speci), accuracy (Accu), precision (Preci), and F1-score [22]. When evaluating the accuracy of positive predictions, sensitivity is employed, whereas specificity is used to assess the accuracy of negative predictions. To determine these metrics, the following equations are utilized:

$$\text{Accu} = \frac{TP+TN}{\text{TP+TN+FP+FN}} \tag{6}$$

$$\text{Preci} = \frac{TP}{TP+FP} \tag{7}$$

$$\text{Sens/Reca} = \frac{TP}{TP+FN} \tag{8}$$

$$\text{Speci} = \frac{TN}{TN+FP} \tag{9}$$

The symbols TP, FP, TN, and FN are used to represent the following concepts:
TP - True Positive,
FP - False Positive,
TN - True Negative,
and FN - False Negative.

The utilization of statistical significance can enhance the level of confidence in research findings, hence indicating the dependability of the issue domain [5].

Ultimately, the ROC curve was shown in order to illustrate the outcomes, while the area under the ROC curve, often referred to as AUC, was utilized to assess the efficacy of the model. The receiver operating characteristic (ROC). The FPR is specifically defined as

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

Table 2 presents a full description of the individual layers of the EfficientNet-B0 baseline network.

The EfficientNet-B0 model is composed of 16 MBConv blocks that exhibit variations in many features, such as kernel size, feature map expansion phase, reduction ratio, and others. The following is a comprehensive outline of the process for the MBConv1,k3 × 3 and MBConv6,k3 × 3 blocks.

Table 2. Total Number of Parameters of EfficientNet B0 to B5

Model	**Resolution**	**Number of Parameter**
EfficientNetB0	224 * 224	4, 978, 847
EfficientNetB1	240 * 240	7, 504, 515
EfficientNetB2	260 * 260	8, 763, 893
EfficientNetB3	360 * 360	11, 844, 907
EfficientNetB4	380 * 380	18, 867, 291
EfficientNetB5	486 * 486	29, 839, 091

Prediction Performance

The predictions of the proposed EfficientNet-B0 are presented in **Table 3**. In the absence of an ensemble, it is observed that the utilization of EfficientNet-B0 with EfficientNet-B5 pre-trained weights leads to better outcomes compared to other base models [23]. This finding highlights the effectiveness of employing an optimized model that incorporates higher depth and width, as well as a wider image resolution, for feature extraction [24]. Consequently, this approach enables the capture of more intricate details, ultimately enhancing the accuracy of image classification and snapshot in **Fig 6** shows Normal and Pneumonia on dataset.

Table 3. Total Number of Parameters of EfficientNet-B0 to B5

Model	Accuracy	Sensitivity/Recall	Specificity	Precision
EfficientNet – B0	96.9	96.58	96.0	96.56
EfficientNet – B1	92.3	93.21	92.26	93.51
EfficientNet – B2	95.3	94.7	95.1	96.3
EfficientNet – B3	95.0	95.2	95.9	96.2
EfficientNet – B4	96.3	96.3	95.35	96
EfficientNet – B5	95.6	95.7	94.9	96.1

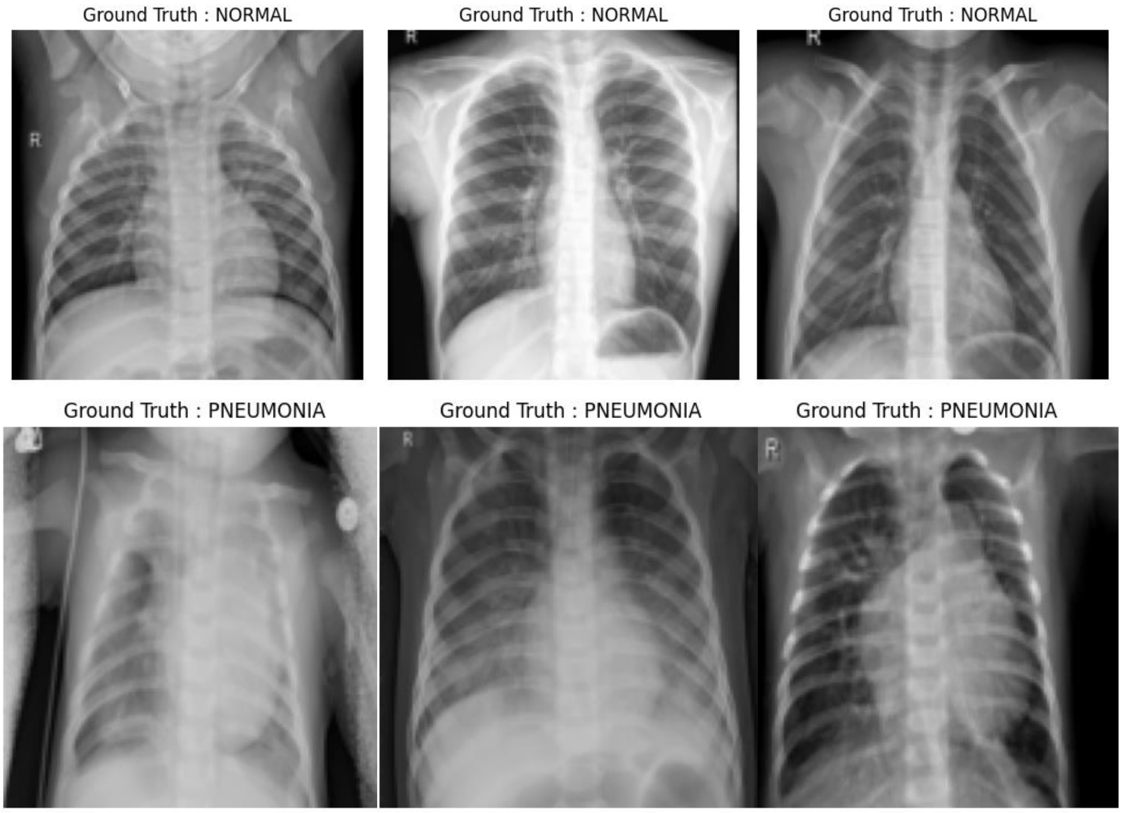


Fig 6. Normal and Pneumonia on Dataset.

The AUC ratings for all categories demonstrate a high level of consistency, suggesting that the suggested model's predictions are reliable and stable.

Comparative of the EfficientNet B0 Model with other Approaches

Table 4 shows how the novel approach stacks up against the most recent techniques for identifying pneumonia from chest X-rays [25]. The findings indicate that the proposed method, specifically the utilization of EfficientNet-B0 with EfficientNet-B5 pre-trained weights for prediction, outperforms other base models in both augmented and non-augmented image scenarios [26]. This outcome suggests that employing an optimized model that considers higher depth and width, as well as a wider image resolution, enables more precise feature extraction, leading to enhanced accuracy in classification. **Fig 7** displays the ROC curves of performance [27]. **Fig 8** shows the Accuracy and Loss curve of EfficientNet-B0 during training and validation function.

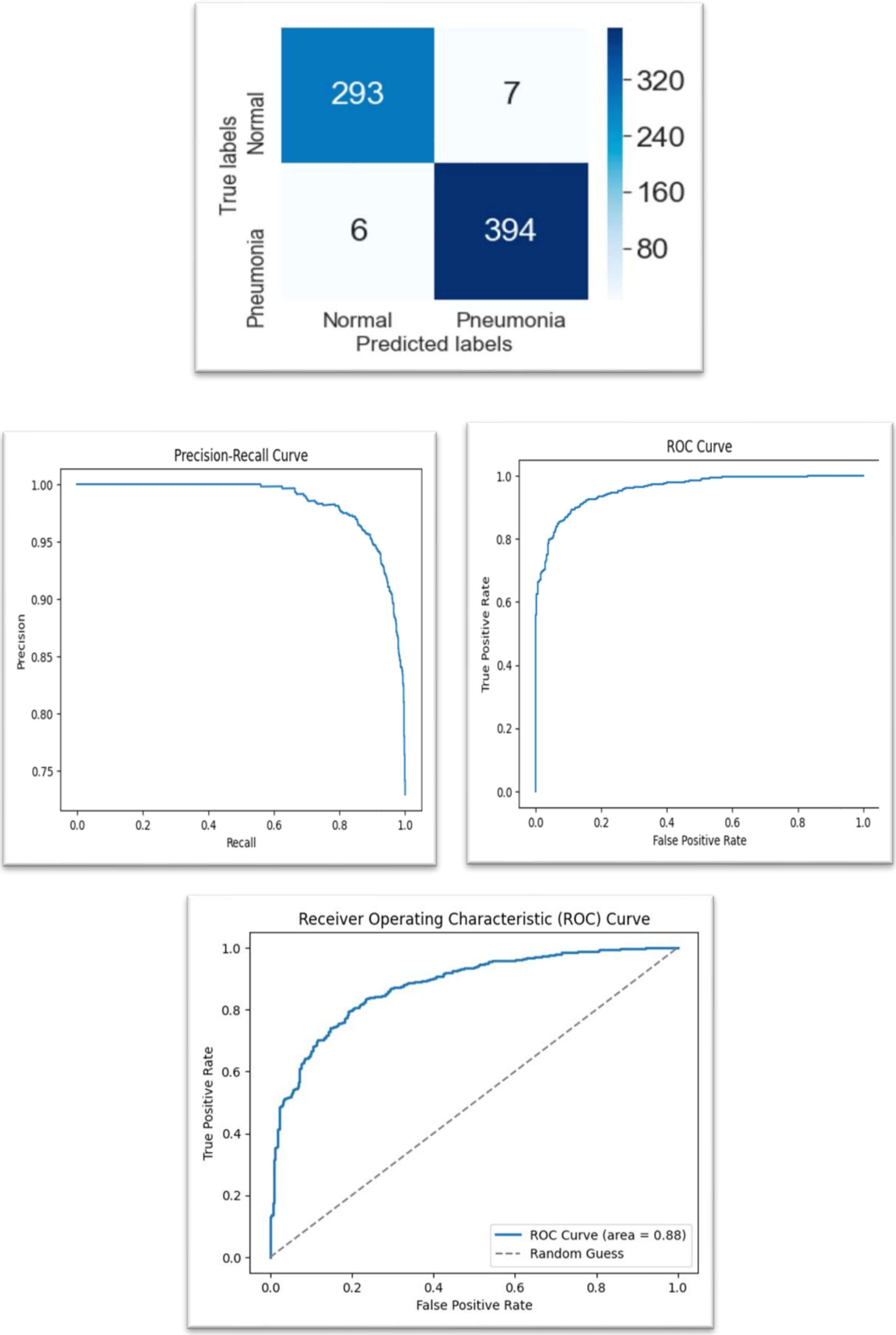
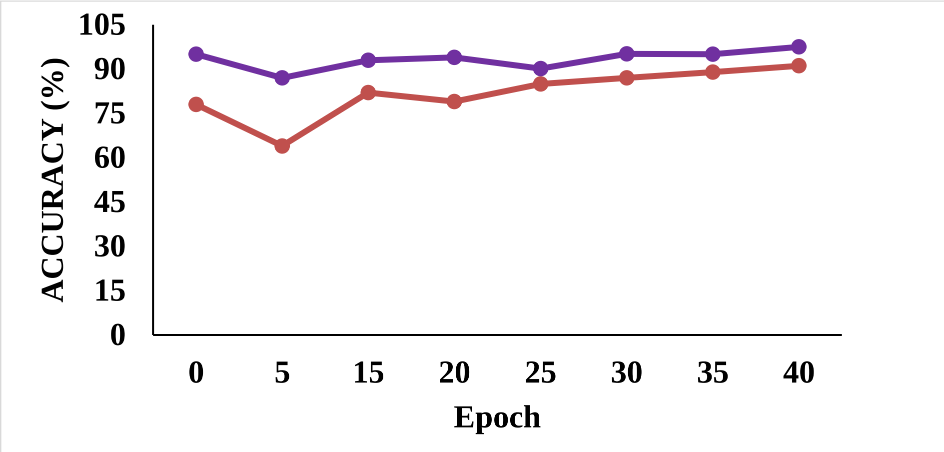


Fig 7. Receiver Operating Characteristic (ROC).



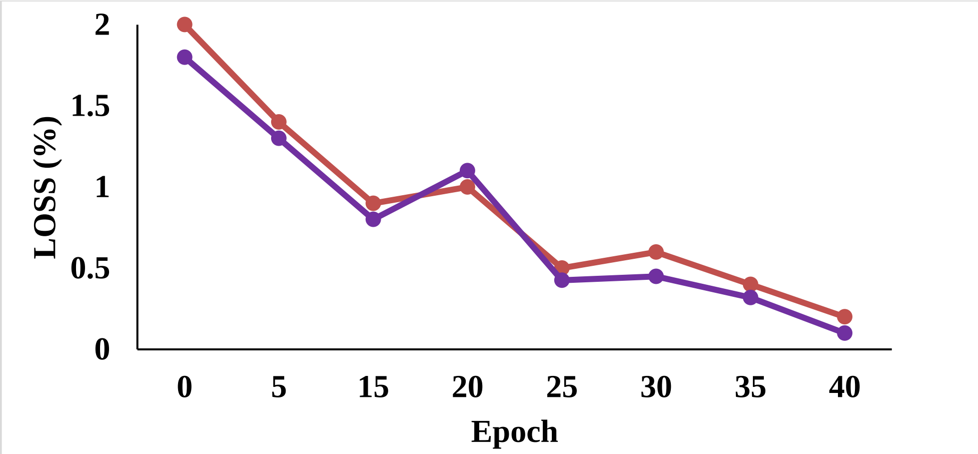


Fig 8. Accuracy and Loss Curve of EfficientNet-B0 during Training and Validation Function.

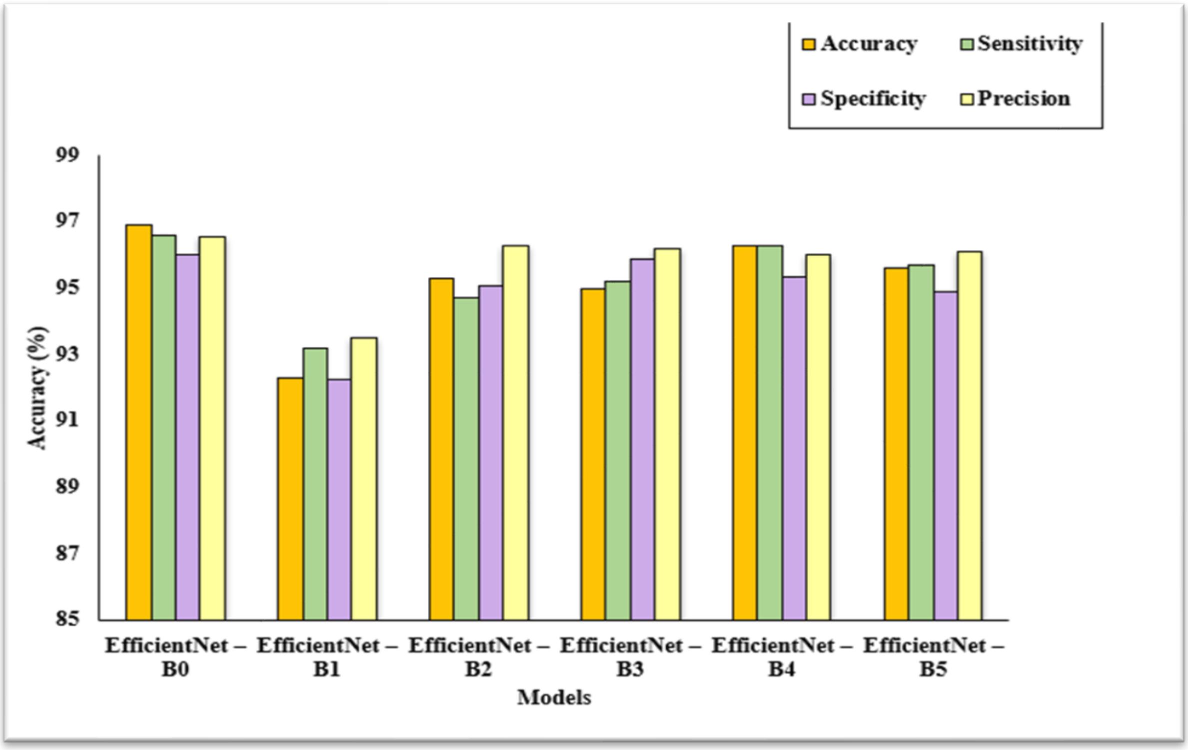


Fig 9. EfficientNet B0-B5.

Fig 9 displays the accuracy, which illustrate achieved by the proposed EfficientNet-B0 model. Several previous methods have been employed in the analysis, including InceptionV3 [28], which achieved an accuracy of 95.1%. Additionally, the ResNet50V2 [29] method was also evaluated, which achieved an accuracy of 93.23%.

Table 4. Comparison Results of the Proposed EfficientNet-B0 with Base Models

Model	Accuracy	Sensitivity	Specificity	Precision
InceptionV3	95.1	95.6	95.02	95
ResNet50V2	93.23	93.1	92.12	93.65
VGG16	85.8	88.8	82.9	85.1
DenseNet121	91.2	80.5	94	77
Xception	91.7	80.1	94.3	76.8
EfficientNet – B0	**96.9**	**96.58**	**96.0**	**96.56**

In contrast, the VGG16 model [22] employed a particular methodology together with a transfer learning approach chest X-rays. The accuracy achieved by this model was 85.8%, while ensuring the preservation of the training and testing datasets. The accuracy of the DenseNet121 approach [30] in a recent study was reported to be 91.2%. This level of accuracy was found to be equivalent to the accuracy achieved by our suggested method, which is capable of reaching 100%. Another approach, known as Xception [31], attained a classification accuracy of 91.7%, falling somewhat short in comparison to the accuracy reached by our suggested method in **Fig 10**.

The proposed model CNN model developed in this study utilizes the EfficientNetB0 architecture and achieves an average recall value of 96.58% in the context of binary classification. In contrast, binary classification reports an average precision of 96.56%. The binary classification model achieved an accuracy rating of 96.9%.

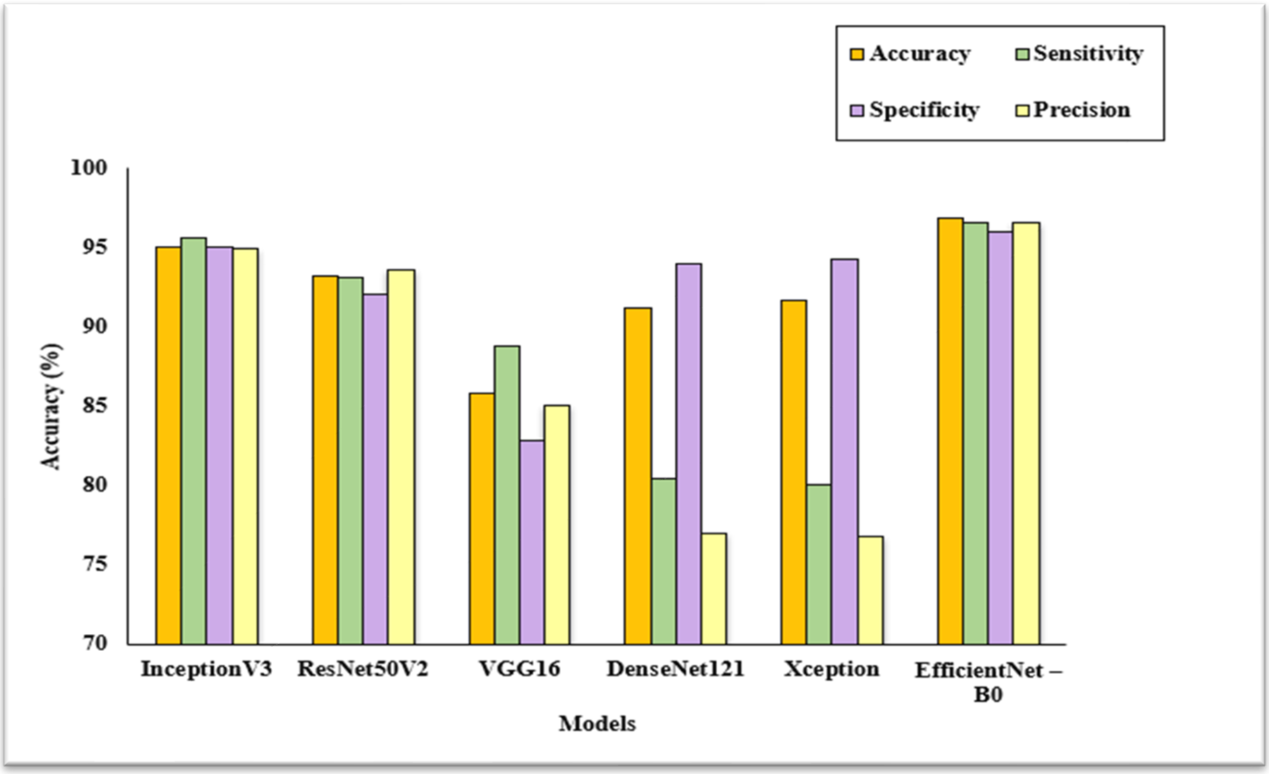


Fig 10. Comparison Results of the Proposed EfficientNet-B0.

V. DISCUSSION

The presence of abnormalities in the upper chest cavity of human beings poses a significant risk to their survival, as these diseases, when at an advanced stage, might lead to the mortality of affected individuals [32]. Academic researchers are currently dedicating their efforts towards the development and implementation of computer-aided systems aimed at achieving accurate and prompt identification of chest disorders through the analysis of X-ray samples. However, there has been a lack of focus on implementing systems that not only classify aberrant chest areas, but also accurately identify the specific location affected by the disease. This capability would greatly aid doctors in conducting thorough examinations and initiating appropriate treatment protocols. The precise and efficient identification and categorization of specific anomalies in the upper chest cavity through the utilization of X-ray pictures poses a challenging task due to the intricate structural characteristics exhibited by these specimens, such as their extensive exposure dynamic range. Additionally, the difficulty of chest disease identification and classification processes is further heightened by the existence of various imaging abnormalities and significant similarities between different classes and within the same class. Furthermore, it amplifies the intricacy of the methods involved in detecting and classifying chest diseases. The findings from both the qualitative and quantitative analyses demonstrate the efficacy of our technique in accurately identifying and categorizing a wide range of chest disorders. Furthermore, the proposed methodology exhibits a high level of resilience in accurately identifying a wide range of image distortions, as well as effectively distinguishing between remarkable similarities within and between different categories.

VI. CONCLUSION

The current methodology introduces a deep learning framework known as the EfficientNet-B0 model, which is utilized for the detection and categorization of chest anomalies based on X-ray samples. EfficientNet-B0 was used to properly determine a unique set of sample key points and classify them in this investigation. In addition, the suggested design demonstrates economic resilience in its ability to classify a diverse range of chest X-ray anomalies. This is achieved through the utilization of a one-stage object identifier, which effectively identifies different chest disorders. The accuracy achieved was 96.9%, while the precision score was 96.56%. The results indicate that the model described in this study outperforms current frameworks in terms of both computational cost and classification outcomes. Moreover, the proposed method demonstrates efficacy in accurately categorizing diverse chest ailments by analyzing the presence of distinct image distortions and significant commonalities within and between categories. The proposed study exhibits an excellent level of performance in the categorization of disorders shown in chest X-ray images.

VII. FUTURE WORK

There exist certain issues pertaining to the preceding EfficientNet series models. One such issue is the considerably sluggish training pace observed in EfficientNet-B3 to EfficientNet-B7 when the image size is substantial. The utilization of Depth wise convolutions results in a decrease in training speed. Utilizing same magnification to enlarge each layer is not the optimal selection. The continuous expansion of image dimensions, accompanied by a corresponding increase in memory usage, directly impacts the efficiency of training processes. Hence, future research endeavors to develop a novel convolutional neural network based on EfficientNetV2. This model has a nonuniform scaling method, enabling an increase in the number of deeper layers. Additionally, it exhibits improved training speed and parameter efficiency when compared to its predecessors.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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There are no competing interests

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