

# EfficientNet-B0-Based Classification of Pneumonic Lungs Using Chest X-Ray Dataset

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**Abstract**— In this research paper, the authors take a new angle: classify pneumonic lungs by utilizing up-to-date architecture such as EfficientNet-B0. Given a huge X-Ray dataset of real cases, the model is excellent at identifying pneumonia. The study aims to address a crucial need in the area of respiratory medicine-through development and application for clinical diagnosis of diseases of the lungs which are efficient, accurate and can be used on everyone. Its strong ability to learn is shown as the model demonstrates an awesome 99.50% training accuracy, checks itself out by verifying results with a validation accuracy of 92.20%, and sits tight under pressure during testing with an accuracy at 99.28%. As a matter of fact, these results serve to remind us that this model is excellent in accurately identifying normal and pneumonic lung conditions. This research not only enriches the growing literature on deep learning techniques in medical image analysis but also offers an extremely valuable tool for health care providers which can rapidly and precisely diagnose pneumonia. The method uses the EfficientNet-B0 architecture, known for its high performance in image classification. The model is built from a rich and diverse Chest X-Ray dataset, ensuring that it can be generalized to different patient populations and conditions of imaging. The study's findings hold promise for improving diagnostic accuracy, lowering human error as well as ultimately transforming patient outcomes in the realm of pneumonia detection by means automated image classification.

**Index Terms**—Transfer Learning, EfficientNet-B0, Pneumonia, Lungs, X-Ray.

## I. INTRODUCTION

As a major health concern today, pneumonia is now shared by our most vulnerable populations. The disease remains the first among mankind's terrors in terms of both death and suffering. An effective diagnosis, must be timely as well as precise. But these days the strain on medical resources is such that other alternatives are needed if diagnoses are to be made quickly and correctly. At present, however, some successful experiments have

integrated advanced technologies such as deep learning into medical imaging. This project is by offering an attainable entry level model of Efficient NetB to research, add some novel results on the road now traveled, and make some daytime homemade producing. Pneumonia presents a variety of images in a patient chest, making the demand on sophisticated diagnostic tools particularly great. This paper uses deep learning methods applied to chest x-rays to detect subtle lesions of pneumonia. As well as offering medical staff a robust and scalable solution in implementing the solution [2], these results can be produced no matter where you them implemented.

At the heart of the approach is the EfficientNet-B0 architecture, well known for its superior performance in image classification tasks. Connecting model complexity with the number of computational resources available, this neural network is well suited for applications in medical imaging where precision and computational resources are crucial. The data used in this study is a mixture of many different types, with diverse age ranges and laborious imaging conditions. Training the model on such a comprehensive dataset ensures that it will be able to transfer effectively and could be suitable for various clinical situations Likewise. The model's training accuracy was 99.50%, with validation and test accuracy rates of 99.20% 99.28% respectively; it is far from useless to hope that this clear clinical potential. As the burden of pneumonia persists globally, this study brings hope for changing the paradigm of diagnosis radically. A highly accurate and efficient tool for classifying lung pneumonic condition will be offered in this study. We hope to improve patient outcomes, shorten diagnosis turnaround times, and further the intersection of deep learning and medical imaging in general. [3]

## II. LITERATURE REVIEW

The most current developments in the use of deep learning techniques for the diagnosis of pneumonia are reviewed in detail in this section.

In medical imaging, the big problem is pneumonia identification. And that's because there are no clear symptoms shown in CT or X-ray scans. In their report [4], P. Szepesi and L. Szilágyi propose a deep neural network architecture which automatically identifies pneumonia. This algorithm was trained on 5856 labelled photographs of young patients taken at the Children's Hospital in Guangzhou, China. With an accuracy rate of 97.2%, recall rate at 97.3%, and exactness 97.4%. It substantially outperformed all current methods. Based on four advanced deep convolutional neural networks already trained with chest X-ray images, their research [5] put forward an automatic identification scheme. Using 5247 chest X-ray pictures the study achieved a maximum classification accuracy of 98%, 95%, and 93.3%, respectively. By monitoring air travel, therefore, it is essential to quickly establish the presence of pneumonia. Chest X-ray pictures are used by R. Kundu et al. [6] in one computer-aided diagnostic method for producing an automatically diagnosed pneumonia. Based on transfer learning methods, three different convolutional neural network models were employed to yield the RSNA and Kermamy databases They achieved accuracy rates of 98.81% and 86.85% respectively. Repeated reliability evaluations and actual use of this approach outperformed those available in today's state of the art – a finding borne out by statistical studies.

The 2019 study by M. B. Darici et al. [7] tried to categorize pneumonia into bacterial, viral and healthy forms -- weathering for their existence in data of chest X-ray image files. The former issue was addressed using the SMOTE approach in order to get balanced datasets and the latter problem was treated by means of CNN and ensemble learning models. The results were that multi-class classification had 78% accuracy with 75% average accuracy or 'class-matched-only' among learned models while binary classification had 95% accuracy after data processing. On digital photographs of the chest taken with X-ray imaging equipment, the paper by M. F. Hashmi et al.'s [8] research proposed a practical model capable of diagnosing pneumonia. Through the method, we combined weighted predictions from mobilenetv3, densenet121, xception, InceptionV3 and ResNet18 deep learning models. Training and validation accuracy are

enhanced by approaches like as transfer learning and partial data augmentation. Using the pneumonia dataset from Guangzhou Women and Children's Medical Centre, the model obtains an AUC score of 99.76 and a test accuracy of 98.43%. The research by S. V. Militante [9] utilised chest X-ray pictures to predict and identify pneumonia cases using deep learning algorithms. AlexNet, VGG-16, StridedNet, GoogLeNet, LeNet, and ResNet-50 are the six CNN models that are used. Using Adam as an optimizer, the models were assessed after being trained on 28,000 photos. According to the findings, ResNet-50 attained 80% accuracy, VGGNet-16 attained 97%, AlexNet and StridedNet attained 96%, and GoogLeNet and LeNet attained 98%. With regard to accuracy, GoogleNet and LeNet models performed best. The convolutional neural networks Xception and Vgg16 was made use of in research by E. Ayan and H. M. Unver [10]; the results were that Vgg16 outperformed Xception with respect to accuracy (82% and 87%). Such results underscore the distinct nature of each network. In the study by K. El Asnaoui [11] versions of Resnet50 that are better optimized are used to assess a series of advanced deep convolutional neural network architectures for automatic binary classification in the case of pneumonia photography. After integrating, the new version performed well with an accuracy of 96% or more, in a dataset consisting of chest X-ray and CT examinations. In the study by N. M. Elshennawy and D. M. Ibrahim [12] took pictures of chest X-rays to find and categorise pneumonia by four deep learning models. Included among these models are Long Short-Term Memory (LSTM), ResNet152V2, MobileNetV2, and a Convolutional Neural Network (CNN). With its accuracy rate, precision, F1-score, recall and Area Under the Curve (AUC) all now standing at 99.22, our recommended framework is a definite improvement in comparison to any previous efforts. These other models in particular perform better than current methods. Since the COVID-19 pandemic now the problem is to come up with effective diagnostic methods. A deep learning method that employs a pretrained AlexNet model can attain also better-than-average scores near perfect precision (93.42%) of accuracy for identifying CXR images from subjects who are COVID-19 positive, when non-COVID-19 but have viruslike symptoms, or bacteria cause pneumonia in humans (in a state of normal health). This is reported by A. U. Ibrahim [13]. A summary of these surveys is shown in Table I.

Table I. Work Done by Previous Authors

S.No	Author Name	Accuracy
1	P. Szepesi and L. Szilágyi [4]	97.2%
2	T. Rahman et al. [5]	98%
4	R. Kundu et al. [6]	98.81% and 86.85%
5	M. B. Darici et al. [7]	95%
6	M. F. Hashmi et al. [8]	98.43%
7	S. V. Militante [9]	98%
8	E. Ayan and H. M. Unver [10]	87%, 82%
9	K. El Asnaoui [11]	96%
10	N. M. Elshennawy and D. M. Ibrahim [12]	99.22%
11	A. U. Ibrahim [13]	93.42%

### III. PROPOSED METHODOLOGY

This section contains a comprehensive and meticulous explanation of the techniques used throughout the research. We provide the dataset used for training our model and give a comprehensive explanation of the preprocessing processes undertaken to prepare it for analysis. The research methodology is shown in Fig.1 as a simplified flowchart. The visual guide aims to provide a comprehensive overview of the sequential methodologies and procedures used in the study. It offers a comprehensive overview of the experimental design and the technique for processing the results.

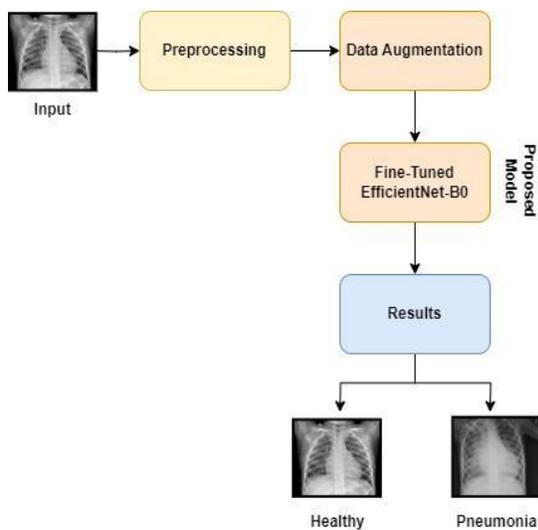


Fig.1 Proposed methodology

#### A. Dataset

In this study, we aim to analyze the distribution of pneumonic lungs in the famous Chest X-Ray dataset [14] built from scratch. It has 5216 images in total. The dataset is mainly binary, with two categories: normal and pneumonia (Fig.2). The normal class has 1341 images that represent X-ray films of healthy people, while the pneumonia class has 3875 images to capture a wide variety of pneumonia patterns. In medical imaging datasets, this binary situation results from the reality of chest shadow and poses a problem for the model. We split the dataset into three parts: training, validation, and testing (Fig.3). The training set makes up 80% of the total dataset and acts as the foundation for the model's learning process. The validation set consists of 12% and is critical to fine-tuning the model during training, optimising its hyperparameters, and mitigating against over-fitting on the training set. The testing set, with 8% of it, is the lynchpin for evaluating how well our model performs in practice and seeing whether it performs accurately on X-ray images that have not been seen before.

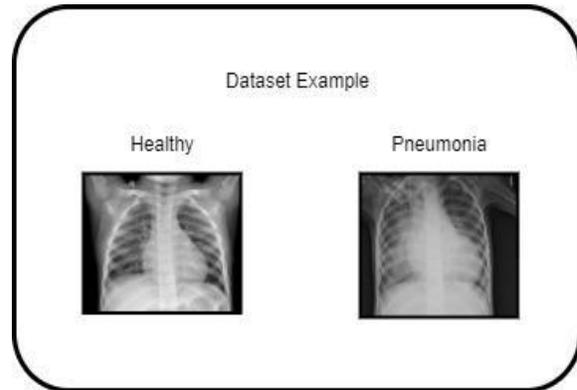


Fig.2. Dataset Classes

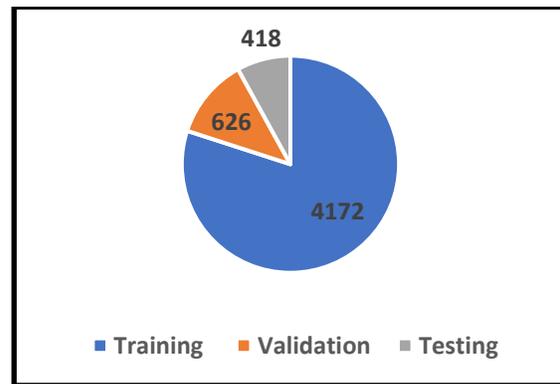


Fig.3. Dataset Distribution

**B. Preprocessing**

In the phase of preparing to train and test model. In this both set sizes for images are standardized at 224 x 224 pixels, greatly simplifying model processing and allowing calculation results on training samples as we shall see later. Dropout, by scaling the learning rate from 0% to 50%, is a way of keeping weights sparse so that they don't become too big. This parameter means that the label is one-hot encoded, making for a clearer perception of the numerical value on which we may base future action. The class mode parameter is functionally similar to output depression's sigmoid activation function in deep learning, it makes our node values or discrete categories respectively. In this work the color mode parameter is set to "rgb", because the images have been processed in a color space which is suited to EfficientNet-B0. Images with uniform color representation simplify training and enable a model to learn from inherently color-specific information contained within the dataset itself.

During the training and validation stages, shuffle is set to True, meaning that the images are switched around at random in each epoch so that the model will not learn patterns from one epoch to a later. This produces more general learning and will shorten links between training data and potential problems or to use an over-trained model for testing; longer test sequences may now be permitted: In comparison, during the test phase, shuffle is set to False. This ensures that the conditions for experimentation are the same every time they are tried. Moreover it also means instead of finding discrepancies purely by chance in one specific batch of images, researchers can indeed observe and record differences more accurately and take them into account in future benchmark test datasets [15].

**C. Model**

Given its superior performance in image classification tasks, EfficientNet-B0 was selected as base architecture model for pneumonia detection in Chest X-rays. As a member of the EfficientNet family of convolutional neural networks, this model is noted for its balanced and scalable design, which is particularly suitable for medical imaging. The characteristic of compound scaling applied in these networks is balancing width, depth, and resolution. This network is a more powerful and computationally efficient way to express models. Chest X-ray images have lots of subtle patterns and characteristics. EfficientNet-B0 is excellent at capture

the very fine, sometimes hard-to-see networks in Chest X-ray images. Its depth and width allow for hierarchical representations of the data, from which it gradually discovered (advanced) there are small-scale changes that could be pneumonia. Moreover, in the model architecture utilized the Batch Normalization can speed up and stabilize training process. By reducing "internal covariate shift" it helps to ensure that gradients don't disappear or explode during backprop The model also frequently uses regularization techniques, mainly inserting Dropout in the model to stop it from overfitting while allowing for generalization. In the final Dense layer, the model uses the Rectified Linear Unit function (ReLU) as activation function. This makes the model have a non-linearity element which is necessary for capturing complex relationships between various features of data. A Dropout layer is then carefully inserted after the Dense layer. During the training process, a proportion of neurons are switched off at random, causing the model to rely on more robust inductive features for recognition. The activation function used in the hit layer is the softmax activation function, which outputs a probability distribution of output classes. This is a critical step for detecting pneumonia (Fig.4). Our choice of EfficientNet-B0, in combination with model-specific architectural components such as Batch Normalization, regularization techniques and suitable activation functions shows it is well suited to perform on this difficult task of pneumonia detection in Chest X-ray images [ 16].

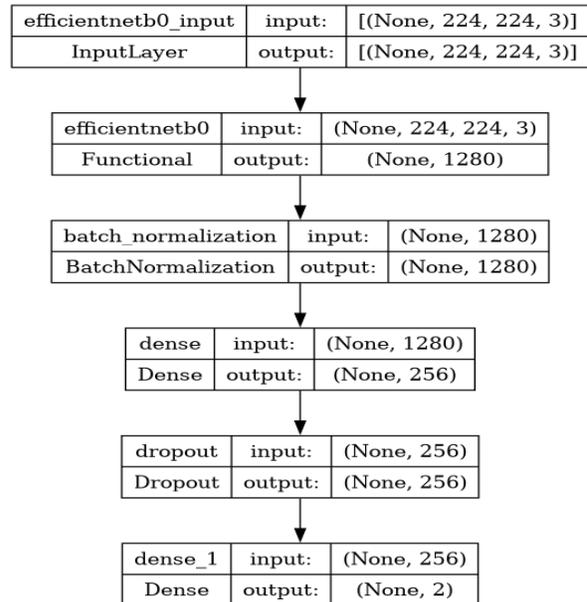


Fig.4. Dataset Distribution

IV. RESULTS

The effectiveness and efficiency of a deep learning model are the primary objectives of this research. The study delves deep into the methodology used to train and assess the model.

The EfficientNet-B0 model is trained for 10 epochs, each of which represents a complete pass through the entire Chest X-ray data set. It is important to maintain this balance between finding complex patterns quickly, without overfitting too much. A batch size of 16 is used during training to achieve computational efficiency and stable operation. As there are 5216 images in the dataset, 261 batches are divided into manageable segments for iterative learning. The model attains a training accuracy rate of 99.50%. This indicates that it is capable of learning and remembering the patterns associated with a normal and infected with pneumonia X-ray image. A corresponding loss rate of 0.1435 is seen during training. A lower training loss signifies that the model's predictions are closer to the actual labels. This not just points up good efficacy but also confirms that the learning process is working. While the model is trained, it is important to measure performance with a dataset other than that which is being used for training in order to ensure generalization ability on unseen data. The validation accuracy for the model is 99.20% (Fig.5), which is a fine result showing that it can make accurate predictions when faced with data it has not seen in training. A somewhat higher validation loss of 0.6173 falls within an acceptable realm as a measure of how well the model is finding new data in unpredictable environments (Fig.6). To sum up, the EfficientNet-B0 model for pneumonia detection in Chest X-ray images is conducted for 10 epochs, with a batch size of 16. And the strikingly high training with relatively low training loss demonstrates its capacity to learn those intricate patterns out of data; also given by such neat cross-validation results is further evidence that clinical applications hold promise.

The test data set is used to give a final evaluation of the performance of the EfficientNet-B0 model after the training phase. After training, it has an model testing accuracy of 99.28%, verifying its correctness in categorizing chest X-ray images as normal or pneumonia. The low testing loss of 0.1349 also shows the model's ability to make accurate predictions for data that has never been seen before. These performance parameters are shown in Table II; they justify the validity

of the model and may be valuable tools for diagnosis at any medical institution wishing to go beyond pneumonia.

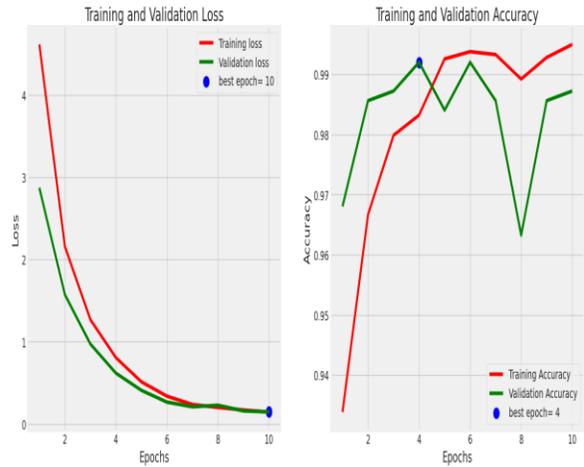


Fig.5. loss graphs.

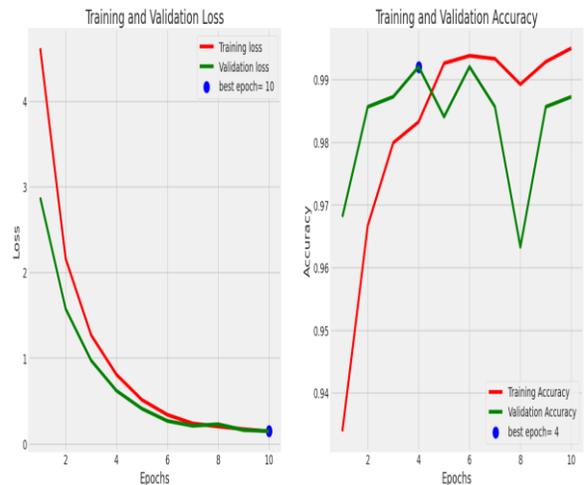


Fig.6. Accuracy graphs.

Table II. Performance Matrix

Classes	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Normal	100	97	98	99
Pneumonia	99	100	100	

Confusion matrix (or error matrix) is a common tool in machine learning for measuring the performance of a classifier. It can also be used to make model predictions and compare them with actual results. It allow for

evaluating model performance, class imbalance, error analysis, threshold adjustment, model selection and comparison, medical or anomaly detection, business strategy adjustments and hyperparameter optimization. It also helps stakeholders make informed decisions by optimizing models and assessing their suitability for real-world applications. The confusion matrix is shown in Fig. 7.

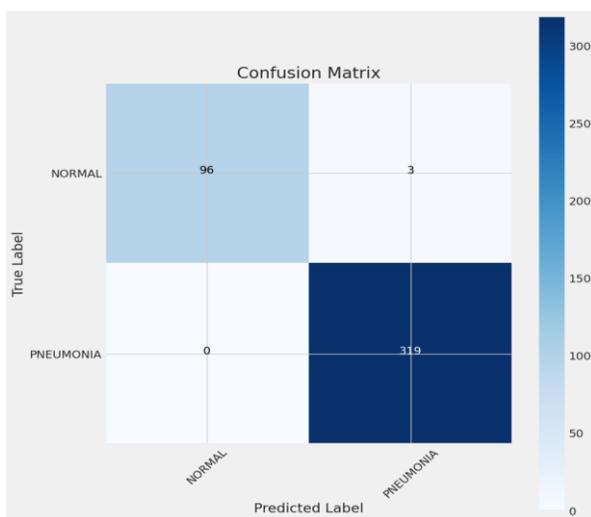


Fig.7. Confusion Matrix

## V. CONCLUSION

A deep learning model based on EfficientNet-B0 was created for classifying pneumonic lungs in Chest X-ray images. The model was developed with an accuracy of training 99.50%, accuracy of validation 99.20%, and accuracy of testing 99.28%. The model architecture, with a total of 5216 images from normal and pneumonia cases, balanced distribution plays a crucial part in training and validation of the system. Because its design is both uniform and scalable, the EfficientNet-B0 architecture was well suited to medical imaging for pneumonia detection. Its model has the capacity to discern subtle abnormalities that are indicative of pneumonia with a sensitivity that can capture even the most delicate intricacies. The model's resilience is further increased by Batch Normalization, regularization techniques and a carefully designed Dense layer. The model achieves a high accuracy on both training and testing. The potential is thus demonstrated for using this model as a tool to automate the detection of pneumonia in chest radiographs. Expansion of the dataset, fine tuning hyperparameters then integrating interpretability and

explainability techniques as well as new ensemble methods are needed. Future research might involve real-world deployment, clinical validation, continuous learning and updates, and multimodal data put into practice. To further improve the model performance, with the capacity of distinguishing between normal and pneumonia-affected cases, underpinning its suitability in clinical applications. Further research and enhancements could involve expanding the dataset, fine-tuning hyperparameters, enhancing interpretability and explainability, investigating ensemble approaches, real-world deployment and clinical validation, continuous learning updating the latest data trends, multi-modal data integrated across various sources of information ingested into one system for use at home in contrast to just doing things individually as accessible from inside or outside sites for you like "one-stop" shopping [17].

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