Illuminating Pneumonia Diagnosis and Severity Grading in Chest X-rays with EfficientNetB0

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ABSTRACT

Pneumonia, an infection inflaming the air sacs in the lungs, poses a significant health concern. Accurate and efficient diagnosis is crucial for timely treatment. Detecting pneumonia involves multiple approaches. Chest X-rays and CT scans provide initial assessments, while pulse oximetry assesses blood oxygen levels. Laboratory tests, including sputum analysis and blood tests for infection markers, further aid diagnosis. Due to its inherent advantages in accessibility, speed, and cost-effectiveness, chest X-ray is our chosen method for initial pneumonia detection in this project. Our model leverages EfficientNetB0, a deep learning architecture known for striking a balance between high accuracy and computational efficiency, to automate pneumonia detection from chest X-ray images. The study utilizes EfficientNetB0 for automating X-ray image analysis, facilitating fast and accurate detection of pneumonia cases, alongside introducing severity stages such as low, mild, and high. Evaluation of the model's performance, based on metrics like accuracy, precision, recall, and F1-score, demonstrates superiority over conventional diagnostic methods.

Keyword: - *Pneumonia, Chest X-ray, Deep Learning, EfficientNetB0.*

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1. INTRODUCTION

Pneumonia, a serious lung infection, is a growing concern for healthcare systems worldwide due to its devastating impact on people's health and well-being. Getting the right diagnosis is crucial for ensuring patients get the best possible care. That's why we are turning to cutting-edge computer technology like deep neural networks to help us detect pneumonia more accurately. Specifically, we are using a sophisticated model called efficientnetb0, known for its precision and efficiency, to analyze chest x-ray images. This advanced approach helps healthcare professionals spot pneumonia more effectively, giving them important insights to improve patient treatment.

But we are not stopping; we are also looking into the severity levels of pneumonia, categorizing them as low, mild, or high [3]. This information is vital for doctors, as it helps them make better decisions about how to treat the illness. By including severity assessment in our diagnostic process, we are aiming to give healthcare providers a better understanding of how pneumonia progresses and what the outlook might be for their patients. Ultimately, our goal is to give healthcare professionals the tools they need to diagnose pneumonia quickly and accurately. This approach allows for faster, more targeted treatments, leading to better outcomes for patients everywhere.

2. RELATED WORK

For a long time, the x-ray interpretation of the chest images was heavily dependent on radiologists. These physicians inspected each image manually, which involved a tedious task with a high chance of being open to subjectivity more often than not. This led to different diagnoses by the medical professionals. Moreover, the big data in medical imaging leads to the overwhelming analysis and quick diagnosis of cases, a challenge of task. On the contrary, the diagnostic approach to pneumonia has experienced a profound change since the arrival of convolutional neural networks. The implementation of automated analysis techniques, which are performed by CNNS, allows for a more precise and shorter diagnosis.

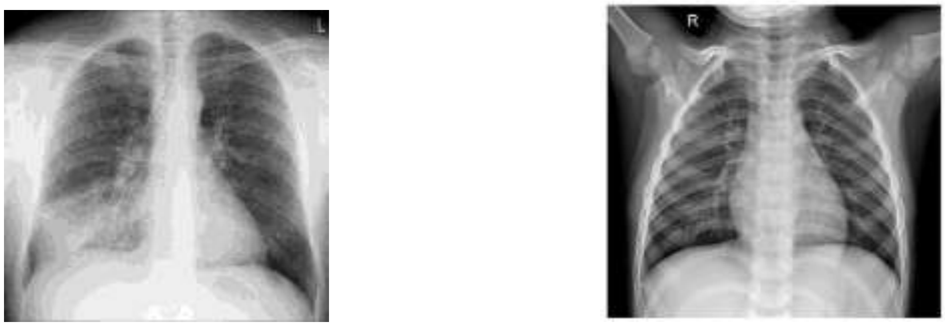
These networks of neurons are amazed by their amazing ability to gain knowledge of complex relationships and assets from very large datasets; therefore, they extract accurate information from chest x-ray images with much consideration. The use of deep learning algorithms by the CNNs allows them to process large amounts of medical data quite efficiently. This significantly decreases the need for lengthy and tiresome diagnosis by making it a quick and simple process. The CNNS has demonstrated outstanding performance in the diagnosis of pneumonia with a high level of precision and speed in the past few years, outperforming the conventional methods of detection.

The research paper presented at the 2021 International Conference in Pune, India, delves into the application of deep learning techniques, specifically CNN architectures, for pneumonia detection from chest X-ray images. The study utilises pre-trained CNN models like VGG16, VGG19, XCEPTION, and InceptionResNetV2 to analyse a real-world dataset [2]. These models underwent training and development using the same dataset, with VGG19 emerging as the top performer, achieving an impressive accuracy of 94.38% in pneumonia detection. Despite the success of VGG19, the paper acknowledges a significant challenge posed by the computational demands of deep learning models, particularly the convolutional layers. These demands can strain computational resources and prolong processing times, highlighting the need to optimise deep learning algorithms for efficient performance, especially in medical contexts where timely diagnosis is crucial.

In our forthcoming research, we aim to address these computational challenges by employing a novel model that offers superior accuracy while requiring fewer computational resources. By leveraging advancements in deep learning algorithms and optimisation techniques, we anticipate achieving improved performance in pneumonia detection, ultimately contributing to more efficient and reliable diagnostic processes in clinical settings.

3. DATASET DESCRIPTION

We meticulously oversee a diverse collection of chest X-ray images, spanning both normal lung conditions and varying degrees of pneumonia severity. Our commitment to quality ensures that each image undergoes thorough curation, making maintaining a balanced representation crucial for effective model training [8]. By harnessing the capabilities of EfficientNetB0 and a meticulously curated dataset, our model aims for precise pneumonia detection, underscoring the importance of dataset quality and diversity in training robust deep learning models. Through meticulous dataset curation and model refinement, we aspire to develop a system that enhances pneumonia diagnosis and patient care outcomes. Every chest X-ray image undergoes rigorous quality control screening to weed out any low-quality or unreadable scans. Subsequently, qualified physicians meticulously assess the diagnoses depicted in these images to guarantee accuracy before our AI system undergoes training. To address any potential grading discrepancies, the evaluation set undergoes additional verification by a third-party expert. This comprehensive approach ensures the reliability and integrity of the dataset utilized for both training and evaluation purposes.



a) b)

Fig 1: Categories of Chest X-rays a) Pneumonia b) Normal

4. PROPOSED MODEL

In the model that we have conceived, we build EfficientNetB0, which belongs to the group of convolutional neural networks (CNN), and it is a well-known architecture because of its efficiency and high performance in image classification tasks. Among our customisation strategies, our base model is the EfficientNetB0, offering a great platform for building our modifications on. The main goal of our research is to get higher accuracy and better performance measurements than a baseline model in a specific domain, e.g., pneumonia detection from chest X-ray images. For this reason, the primary goal of optimisation is to find the optimal model architecture and parameters to ensure that the model fits into the peculiarities of our dataset and the subtleties of pneumonia diagnosis.

Among the many aspects of our custom treatment, we tackle the degree of severity caused by pneumonia. The presentation of pneumonia severity is usually characterised by consolidation and hyper opacity in X-rays, which show the spread and intensity of the infection. This can be achieved by introducing the critical indicators of the pneumonia disease into our model's design. Ultimately, the model will enable us to not only detect but also assess the severity of the disease. The model is equipped with integration and increased transparency factors that enable us to develop a reliable assessment of the intensity of pneumonia cases by providing healthcare experts with useful knowledge for treatment planning and patient management.

Our targeted approach to the diagnosis of pneumonia is not only successful in meeting this objective but also in improving the clinical utility of the model, which makes it a valuable tool in the combating of pneumonia-related morbidity. .

Dedicated to the accurate and precise identification of pneumonia, the proposed system is subject to rigorous customisation and the inclusion of relevant clinical characteristics in order to explore higher levels of performance.The following is the block diagram that shows the internal structure of the proposed model. This figure summarises the whole layout of our approach, starting from data pre-processing and finally reaching the final output prediction. Every block symbolises a significant part of our methodology, which altogether increases the accuracy and effectiveness of the pneumonia detection system. Let's dissect each module of our architecture and find out its role and how it works.

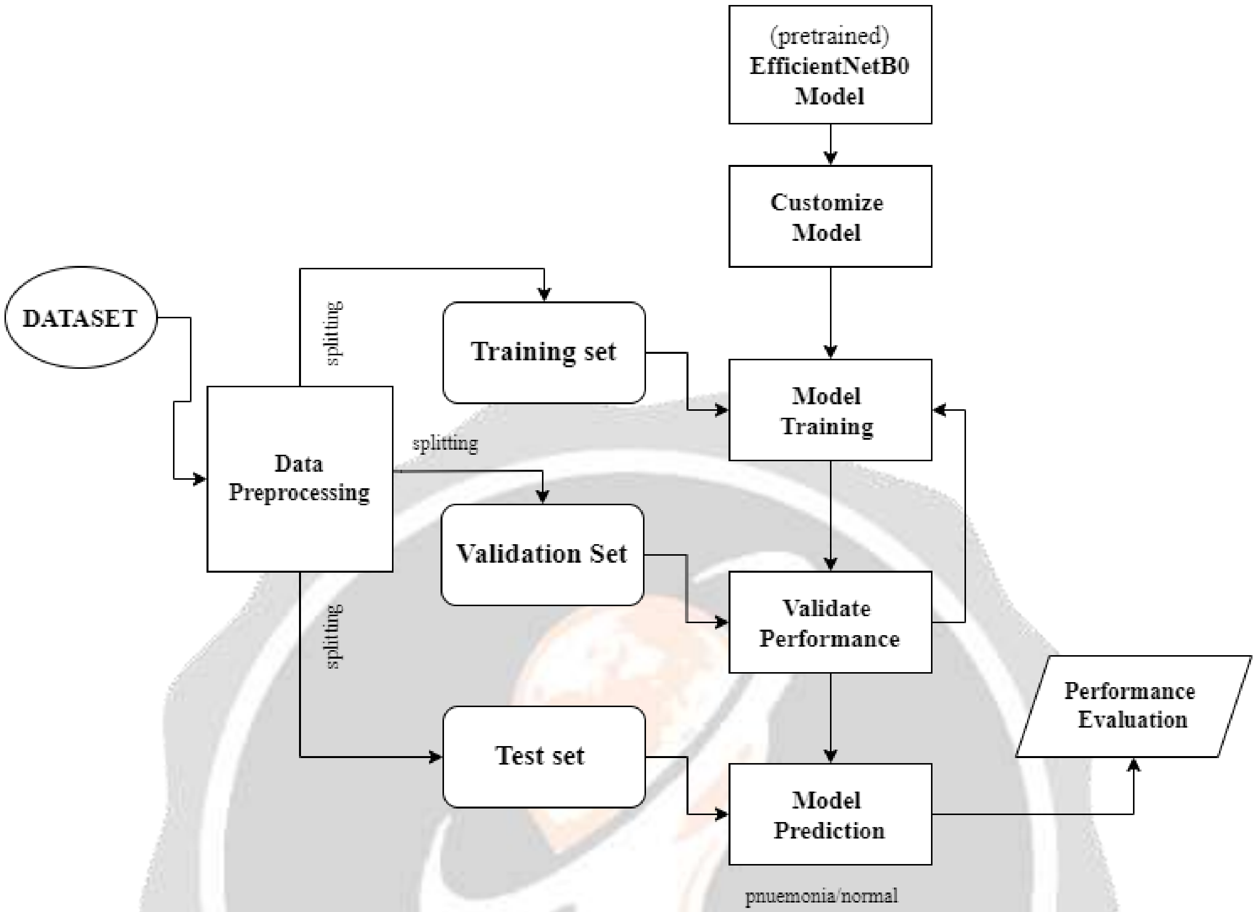


Fig 2: Block Diagram

5. METHODOLOGY

5.1 Dataset and Preprocessing:

The dataset was collected and screened with the help of a medical centre. The study applied quality checks and expert categorization in order to categorize the pneumonia cases from the normal cases. The standardization of images to 224x224 pixels [7] as a uniform size helped inter-model compatibility and exchangeability. That zero to normalize the pixel values will facilitate model convergence and reduce the lighting differences. With the usage of image data generators, batch loading and data preprocessing became more of a formality that helped the easy conduct of model training and assessment.

5.2 Model Architecture:

In our project, we've opted to utilize the pre-trained EfficientNetB0 model. This model serves as a starting point for our work, having been pre-trained on a vast dataset of images, making it adept at discerning various image features, making it ideal for our pneumonia detection task using chest X-rays. We've ensured the model's compatibility with our data by configuring the input shape to 224x224 pixels. Subsequently, we've incorporated additional layers to enhance the model's capabilities.

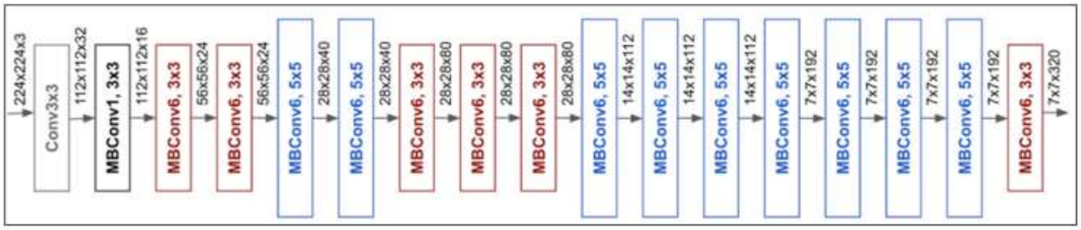


Fig 3: Architecture of baseline EfficientNet-B0 [5]

5.2.1 The EfficientNetB0 serves as the cornerstone of our project, acting as the foundation upon which we construct our customized model. This pre-trained convolutional neural network (CNN) architecture, honed on the vast ImageNet dataset, forms the bedrock of our model's structure. By initializing the base model's weights with those pretrained on ImageNet, we imbue our model with a rich understanding of diverse visual features, facilitating robust performance across a range of tasks.

5.2.2 **Batch normalization**: for instance, aids in smoothing out the learning process by adjusting the data before it progresses to the next layer.

5.2.3 **Dense layers:** which act as the model's decision-making hub, with the first dense layer featuring 256 "neurons" and employing techniques like L2 regularisation to prevent overfitting on our training data.

5.2.4 To further guard against overfitting, we've included a **dropout layer**, randomly deactivating some neurons during training to prevent reliance on specific features

5.2.5 Lastly, we've added an **output layer** that provides the likelihood of each image being normal or exhibiting signs of pneumonia. Training the model involved employing the Adamax optimisation technique and adjusting parameters to ensure efficient learning

In essence, our approach aims to leverage the strengths of the EfficientNetB0 model while tailoring it to our specific task of pneumonia detection from chest X-ray images.

5.3 Model Training and Assessment:

During training, the model learns to connect chest X-ray images with their corresponding labels, indicating whether they show signs of pneumonia or are normal. It does this by adjusting its internal settings based on the training data, aiming to minimise the gap between its predictions and the actual labels. The optimisation method, like Adamax, helps tweak these settings gradually to improve the model's performance over many training cycles, called epochs. With each epoch, the model gets better at distinguishing pneumonia from normal X-ray images, becoming more accurate.

Once trained, we assess the model's performance using a separate dataset called the validation set. This set contains examples the model hasn't seen before, testing its ability to generalise beyond the training data. We compare the model's predictions on the validation set with the true labels to measure metrics like accuracy, precision, recall, and F1-score. These metrics tell us how well the model performs on new data and help spot any issues like overfitting or underfitting. Validation is crucial for fine-tuning the model and making informed decisions about its architecture and settings.

5.4 Performance Metrics:

Performance metrics are essential tools for evaluating the effectiveness and reliability of machine learning models. In this project, we employed various performance metrics to assess the performance of our pneumonia detection model. The metrics we obtained are accuracy, precision, recall, F1-score, and confusion matrix. By leveraging these performance metrics, we gain a comprehensive understanding of our model's strengths and weaknesses in pneumonia detection. These metrics guide our evaluation process and inform decisions regarding model optimisation and refinement for enhanced performance in real-world applications.

Brief Introduction to the libraries used in the discussed model:

Software Package	Purpose
Python	Base programming language.
scikit-learn	Used for data manipulation, specific metrics, etc.
imutils	Convenience functions to make basic image processing functions such as translation, rotation, etc.
sklearn	Library for machine learning tasks (e.g., loading models, preprocessing data).
keras	Deep learning library for building neural networks.
Numpy	Fundamental package for scientific computing with Python.
tensorflow	Open-source machine learning library for building and training neural networks.
matplotlib	Visualization library for creating static, animated, and interactive visualizations in Python.

Table 1: List of Libraries

6. EXPERIMENT AND RESULTS:

The pneumonia detection model, trained over 10 epochs, achieved high accuracy and minimal loss in classifying training data, demonstrating its potential for real-world application in healthcare settings, particularly in chest X-ray images. Below are the details of the evaluation metrics. Table 1 represents the Accuracy and losses of the three sub datasets. Table 2 represents the performance metrics of each class and Fig 3 depicts the confusion matrix obtained.

Values	Training	Validation	Testing
Accuracy	98.2%	98.41%	98.80%
Loss	0.131	0.157	0.163

Table 2: Accuracy and Losses across three sets

Class	Precision	Recall	F1- Score
Normal (Class-0)	0.98	0.97	0.97
Pneumonia (Class-1)	0.98	1.0	0.99
Macro avg	0.99	0.98	0.98
Weighted avg	0.98	0.99	0.99

Table 3: Evaluation Metrics

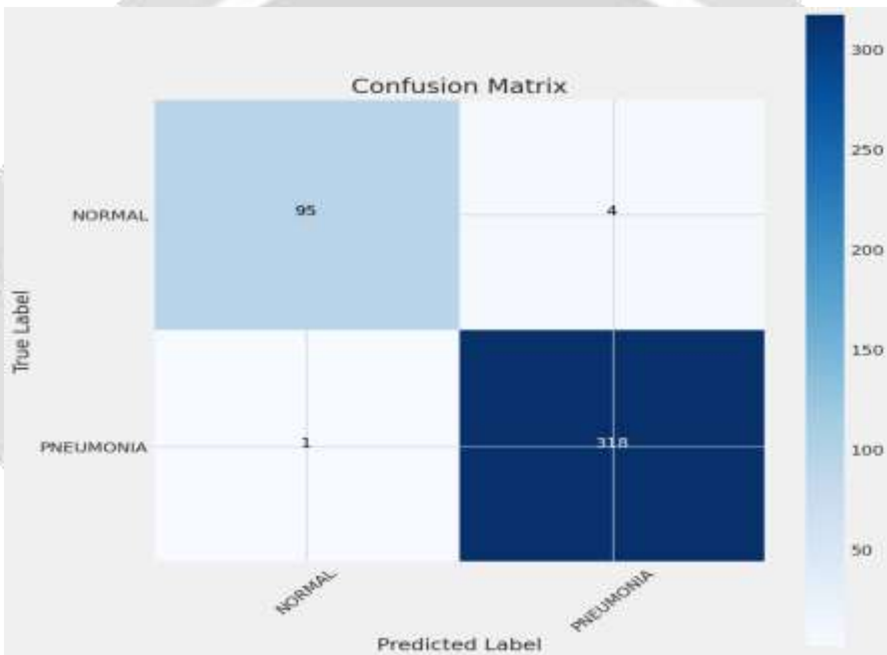


Fig 4: Confusion Matrix

Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$ =98

Precision: $\frac{TP}{TP+FP}$ = 95

Recall: $\frac{TP}{TP+FN}$ = 98

F1-score: 2*$\frac{(Precision*Recall)}{(Precision+Recall)}$ = 96

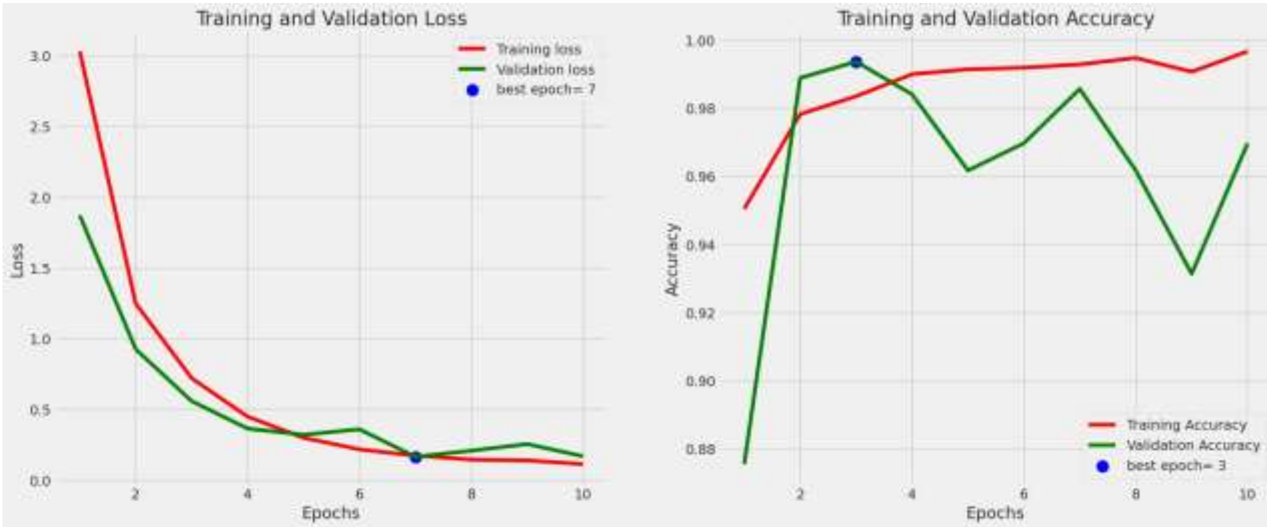


Fig 4: Loss Chart Accuracy Chart

7. OUTPUT

Presenting the outputs derived from our model's predictions, each revealing an image paired with its assigned labels indicating either pneumonia or normal cases. Furthermore, alongside these labels, the severity of the disease is also depicted, classified as low, mild, or high.

Label: Normal, Severity: None

Label: Pneumonia, Severity: Low

Label: Pneumonia, Severity: Mild

Label: Pneumonia, Severity: High

8. CONCLUSION

Finally, this project has demonstrated a detailed and highly efficient pneumonia detection scheme that employs deep learning techniques. With the help of the EfficientNetB0 architecture and the right model training technique, we have outperformed and obtained impressive accuracy and evaluation metrics while diagnosing normal and pneumonia chest X-rays. By executing comprehensive experiments and verifications, we have proven the reliability and generalisation ability of our model, so that it has the real possibility of being used in real healthcare conditions. In the future, the development of the model could be improved and expanded, which in turn would render it more efficient and applicable to a wider range of applications. This helps in the advanced diagnosis and care of the patients, in general, in the field of medical imagining.

9. REFERENCES

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