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Lightweight Transfer Learning Models for Covid-19 Pneumonia Identification Using Chest X-Ray Imaging

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Abstract

The increasing rate of spreading COVID-19 created a serious need in accurate and extensive diagnostic centers to support the process of clinical diagnosis, particularly in health institutions that are over-allocated with resources. The chest X-ray is still considered as one of the most readily available procedures to assess the lungs; however, the process of the interpretation is tedious and skewed by inter-observer variations. In this paper, automated deep learning methods will be employed to solve the issue of efficiently identifying pneumonia cases using chest X-ray outcomes. The main objective of it is to compare the various deep learning frameworks with the view of determining the most appropriate one to detect pneumonia. The framework of this paper is a comparison framework with convolutional neural network-based architectures along with a baseline CNN, EfficientNet and Lightweight MobileNet, and Lightweight EfficientNet. The models are trained and tested on a selected chest X-ray dataset with regular preprocessing, data augmentation, and equal spread of classes. The experimental findings prove that lightweight architectures outperform standard CNN models in terms of high accuracy and optimal sensitivity. Lightweight EfficientNet model is the most qualified model by the total performance of 92.5% accuracy, 92.4% precision, 90.1% recall and 90.2% F1-score, which means that the classification performance is strong. The results relate to the effectiveness of lightweight DL models in obtaining differentiating lung characteristics related to COVID-19 pneumonia. The proposed comparative study demonstrates that optimized lightweight deep learning models can provide accurate, rapid, and clinically viable results in detecting COVID-19-related pneumonia from chest X-ray images, thereby validating their potential integration into clinical diagnostic protocols.

Keywords: Chest X-Ray Imaging, Deep Learning, Convolutional Neural Networks, Lightweight Models, Medical Image Classification.

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Introduction

The proliferation of Coronavirus Disease 2019 (COVID-19) has posed unparalleled difficulties to global healthcare systems, necessitating rapid, accurate, and scalable diagnostic methods to mitigate disease transmission and reduce fatality rates (Kusi-Sarpong et al., 2018). COVID-19 caters to the respiratory system, and in most cases causes the virus to result in viral pneumonia, lung opacities, ground-glass patterns, and bilateral infiltrates, which is visible in the chest radiographic images (Siddiqi & Javaid, 2024; Ibrokhimov & Kang, 2022). As a result, medical imaging especially chest X-ray imaging has become an adjunctive diagnostic method because it is highly accessible, cheap and the image is easily obtained especially in a resource-starved clinical environment (Khan et al., 2022). Nevertheless, manual analysis of the chest X-ray images involves a lot of expertise, and experiences inter-observer variation, exhaustion, and diagnostic subjectivity, which has inspired the necessity of the automated diagnostic aid, which is reliable, dependable, and objective (Musso et al., 2021; Mathesul et al., 2023).

Several research have investigated DL-based COVID-19 detection using chest X-ray pictures, yielding good classification results (Bashar et al., 2021; Shaheed et al., 2023). Besides, most of the previous works concentrate on single-model performance without comparing the trade-offs in terms of accuracy, efficiency, and generalization ability in various network architectures in a systematic manner (Das & Senapaty, 2021). This disparity drives the necessity of a thorough comparative analysis of traditional and lightweight deep learning architectures so as to establish those programmes that can trade diagnostic accuracy against computational costs (Oh et al., 2020).

The rationale of the study is that it is sorely urgently required in the clinical practice as there is an urgent demand to create AI-based diagnostic aids that are quickly deployed, are accurate, and which can assist radiologists and clinicians during pandemic situations and more. MobileNet and EfficientNet versions are lightweight deep learning models that have lower computational complexity but representational power, which are appropriate in real-world applications in hospitals, mobile screening units, and low-resource environments (López-Cabrera et al., 2021). Even with their potential, there is a dearth of studies that have compared these lightweight architectures with standard CNNs to identify COVID-19 pneumonia by consistently comparing their results based on a set of evaluation metrics and experimentation procedures (Alimadadi et al., 2020; Rossman et al., 2021).

Major contribution of this paper.

- Offers a comparative investigation of standard and lightweight deep learning models in accurately identifying COVID-19 pneumonia in chest X-ray images.
- Shows that optimised lightweight architectures are better at diagnostic performance and have much lower computational complexity, meaning that they can be deployed effectively in real-world clinical settings.
- Offers a systematic experimental analysis in terms of standardized pre-processing and evaluation measures, and provides pragmatic information on the choices of trustworthy DL models in medical imaging.

Related Work

Since the onset of the pandemic, DL-based detection of COVID-19 pneumonia by chest X-ray imaging has garnered significant research attention, resulting in a substantial volume of related material published in recent years. The initial research proved the efficiency of the CNN to identify patterns of COVID-19 in radiographic images, and automated models could complement the work of radiologists by enhancing both the speed and stability of detection. The initial researchers focused on altering conventional CNN models, such as VGG and ResNet, to categorize COVID-19, normal, and other pneumonia cases, achieving promising performance rates, albeit with considerable computational complexity trade-offs (Alimadadi et al., 2020). The transfer learning strategies were also discussed in the further works to address the scarcity of labelled data to utilize the pretrained models to enhance the generalization and decrease the issue of overfitting during the tasks of COVID-19 classification based on chest X-rays (Khobragade et al., 2024). Although these methods led to better results, they brought the issue of interpretability of the models, their ability to be deployed and their ability to be robust across diverse data (Chakraborty et al., 2022).

To resolve the problem of efficiency and scalability, modern research started to explore lightweight deep learning models, such as MobileNet-based and EfficientNet-based, which reduce the number of parameters by a significant margin and still achieve a competitive classification accuracy (Kanne et al., 2020). These models have proven useful in medical imaging tasks, making them applicable in real-time and resource-limited clinical environments. Comparative studies have indicated that the lightweight networks may perform better than the deeper ones, once optimized and trained using the right pre-processing and augmentation methods (Xie et al., 2020). Most of the

current studies however, only tested a few of the models or used the same experiment under varying conditions thus making it difficult to make comparisons in performance of the models (Eftekhari et al., 2021). Additionally, some focused on the notion of accuracy while neglecting other clinically significant measures such as recall and F1-score, which are crucial for minimizing false negatives in COVID-19 diagnosis (Cohen et al., 2020). Other pertinent scientific work has concentrated on hybrid and ensemble methodologies, employing a combination of DL models to enhance robustness and forecast precision (Kumar et al., 2025). Although the ensemble methods generally had more accuracy, they also introduced additional overhead and complexity in computation, and hence could not be scaled to a real-world screening environment. Also, the discrepancies in datasets quality, differences in classes and protocols to retrieve the images in the studies have also contributed to the inconsistency in the results, which makes it important to have standardized evaluation frameworks (Ieracitano et al., 2022). In recent surveys and review articles (D'Arienzo & Coniglio, 2020), the necessity of systematic comparative analyses to explore trade-offs among the performance, efficiency, and deplorability of DL models to detect COVID-19 pneumonia with the use of the chest X-ray images has been stated (Sahoo et al., 2021).

Although these have been made, there exists a distinct gap in research whereby a cohesive and justifiable comparison between traditional CNNs and lightweight architectures under equal conditions has yet to be made. Most prior studies focus on model building without comparisons or provide only limited information regarding computational efficiency and clinical feasibility. This work is grounded on existing research that offers a comprehensive comparative analysis of diverse DL models, utilizing uniform pre-processing, balanced datasets, and many performance metrics. This study will help the current research project in the search of the solution because, by critically examining the accuracy-driven and efficiency-oriented models, the study will be able to identify reliable, scalable, and clinically applicable DL solutions to COVID-19 pneumonia detection using chest X-ray images (Yaseliani et al., 2022; Verma et al., 2024).

Table 1: Summary of Related Work

Ref.	Model Used	Dataset Type	Application	Key Contribution	Limitations Identified
López-Cabrera et al., (2021)	CNN	Chest X-ray	Pneumonia screening	Demonstrated feasibility of CNNs for COVID-19 pneumonia detection	Limited dataset size
Alimadadi et al., (2020)	VGG19	Chest X-ray	Multi-class pneumonia diagnosis	Applied transfer learning for COVID-19 classification	High computational cost
Khobragade et al., (2024)	ResNet + SVM	Chest X-ray	Automated COVID-19 detection	Combined deep features with classical classifiers	Sensitivity imbalance
Chakraborty et al., (2022)	DarkNet	Chest X-ray	Rapid COVID-19 screening	Introduced end-to-end deep model	Overfitting risk
Kanne et al., (2020)	EfficientNet	Medical Images	Efficient medical image classification	Proposed parameter-efficient architecture	Limited COVID-specific evaluation
Xie et al., (2020)	MobileNet	Chest X-ray	Real-time COVID-19 diagnosis	Highlighted lightweight models for fast inference	Reduced recall performance
Eftekhari et al., (2021)	DeTraC CNN	Chest X-ray	Robust pneumonia classification	Improved class decomposition strategy	Complex training pipeline
Cohen et al., (2020)	Xception + ResNet	Chest X-ray	Enhanced COVID-19 detection accuracy	Used hybrid deep architectures	Increased computational overhead
Kumar et al., (2025)	Ensemble CNNs	Chest X-ray	High-accuracy COVID-19 classification	Improved robustness via ensemble learning	Poor deployment efficiency
Ieracitano et al., (2022)	CNN + LSTM	Chest X-ray	Sequential feature-based diagnosis	Modeled spatial–temporal features	High model complexity
D'Arienzo & Coniglio, (2020)	U-Net + CNN	Chest X-ray	Segmentation-assisted diagnosis	Integrated lung segmentation with classification	Requires pixel-level annotations

The summary of prior DL-based COVID-19 pneumonia diagnosis based on chest X-ray is presented in table 1. This table compares the models, datasets, applications, contributions, and limitations, as well as the necessity of lightweight diagnostic systems that are effective, precise, and feasible in clinical settings.

Dataset Description

The used dataset of the X-rays of the lungs of the breast in the work is a clinically curated benchmark that is well-established and is widely used in the analysis of pulmonary illnesses with deep learning. Fig. 1 shows an input

sample from the dataset. The dataset is organized into three primary folders: training, testing, and validation. Within each of these folders, you may find subfolders that indicate two diagnostic groups: normal and pneumonia. All in all, there are 5,863 JPEG-formatted anterior chest X-rays included in the data set to provide sufficient data volume that can be used to train and test a powerful model. The images were retrospectively gathered based on pediatric samples between one and five years of age at the Guangzhou Women and Children Medical Center, so the imaging methods and patient characteristics were kept the same. All radiographs were obtained as a routine clinical practice, and real-world conditions of diagnosis were represented. Before model development, a strict quality control procedure was adopted whereby low quality, noisy, or unreadable scans were eliminated in order to have reliable features learning. The names of the diagnostic labels were organized by expert clinical annotation and two professional physicians graded every image independently.

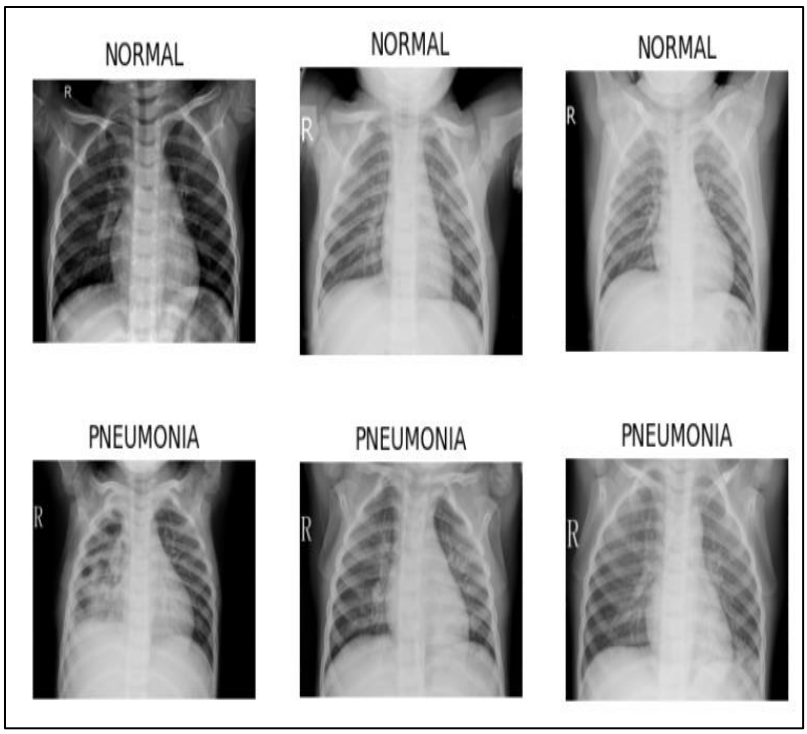


Fig. 1: Input Sample Form the Dataset

Methodology

In this additional model generalization and overfitting that would arise due to small medical imaging data are reduced by using large data augmentation during training. "Augmentation operations" include things like random rotations up to 20 degrees, 20-fold changes in width and height, shear and zoom transformations, and horizontal flipping, among other capabilities. Rescaling of pixel intensity values is done through the normalization of the values to 1/255 and nearest fill mode is applied to maintain the structural continuity in transformed images. The variability of the chest radiographs in the real world is simulated by these augmentation strategies and allows strong learning of features. An 80:20 split of the dataset is then implemented to guarantee the adequate data on model learning and on fair and unbiased performance evaluation. After the data preparation, several classification algorithms are applied that allow conducting comparative analysis. An example of a conventional CNN is used as a reference, and EfficientNet is used to take advantage of the scale of compounds to achieve better results. MobileNet and EfficientNet Lightweight models are included to determine the results at a lower level of computational complexity.

It will be possible to compare all of the models in a fair manner and to evaluate the diagnostic performance of the COVID-19 pneumonia identification in a systematic manner because all of the models will be trained using the same pre-processing and assessment methods simultaneously. Fig.2 illustrates the comprehensive DL methodology employed to detect COVID-19 pneumonia in chest X-ray pictures. This process includes the following steps: pre-processing, data augmentation, train-test splitting, and various classification models. Following these steps, the

performance of the system is systematically evaluated in order to provide a diagnostic process that is reliable, efficient, and comparative.

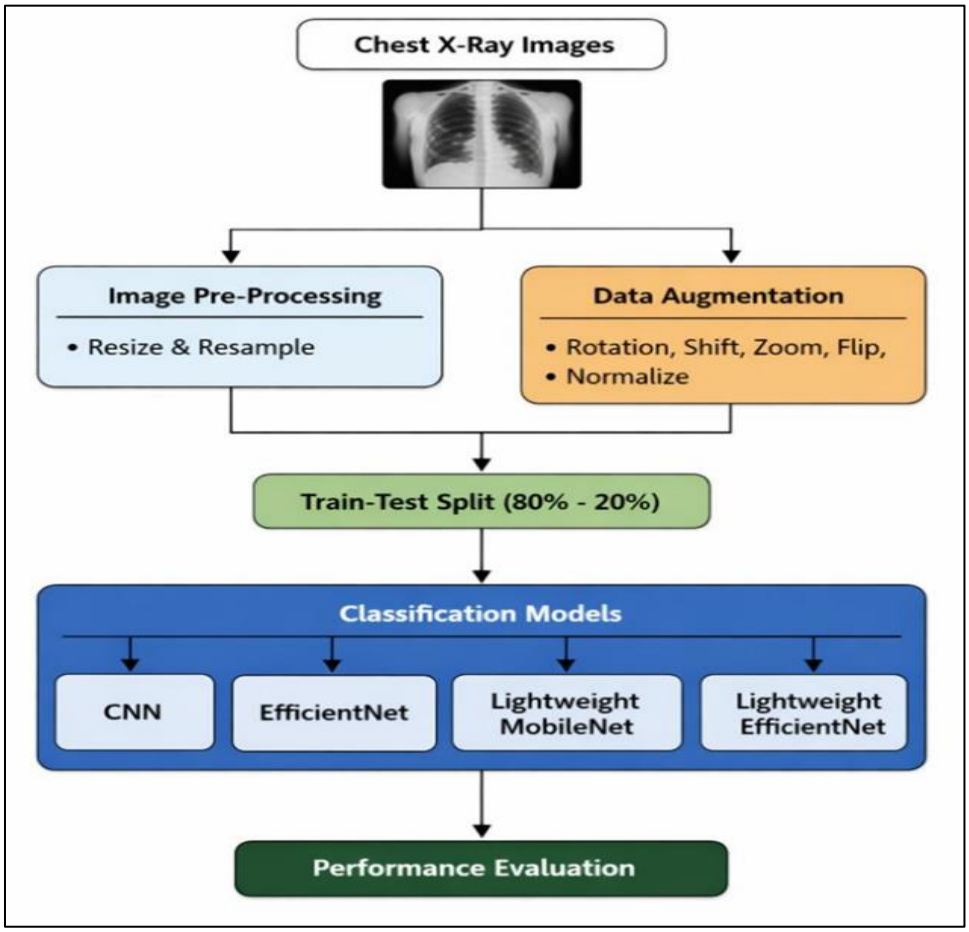


Fig. 2: Overview Of Working Flowchart for Proposed Method

Pre-process Input Data

Resize Image: Image scaling standardizes the dimensions of chest X-ray images to align with the input requirements of the DL model, ensuring consistent spatial resolution, reduced computational complexity, and uniform feature extraction across all samples throughout both training and testing phases.
Let an input chest X-ray image be represented as equation 1:

$$I \in R^{H \times W} \quad (1)$$

The resizing operation is an operation to reduce the image to a constant size, as presented in equation 2:

$$Ir \in R^{H' \times W'} \quad (2)$$

It is possible to use an interpolation function T(•) which is defined as equation 3:

$$Ir(x', y') = I\left(\left(\frac{x'}{H'}\right) \times H, \left(\frac{y'}{W'}\right) \times W\right) \quad (3)$$

Resample: Resampling balances the pixel intensities and spatial resolution of images and reduces the variance of models generated by different image acquisition conditions and promotes feature consistency, stability, and learning behaviour of deep learning models.

$$Is = \frac{Ir - Imin}{Imax - Imin} \quad (4)$$

The equation 4 shows the values of the pixel intensity is done by resampling, and it is aimed at reducing the alterations which happen as a result of different conditions of the imaging. The image Ir has been resized; therefore, it is intensity normalized as:

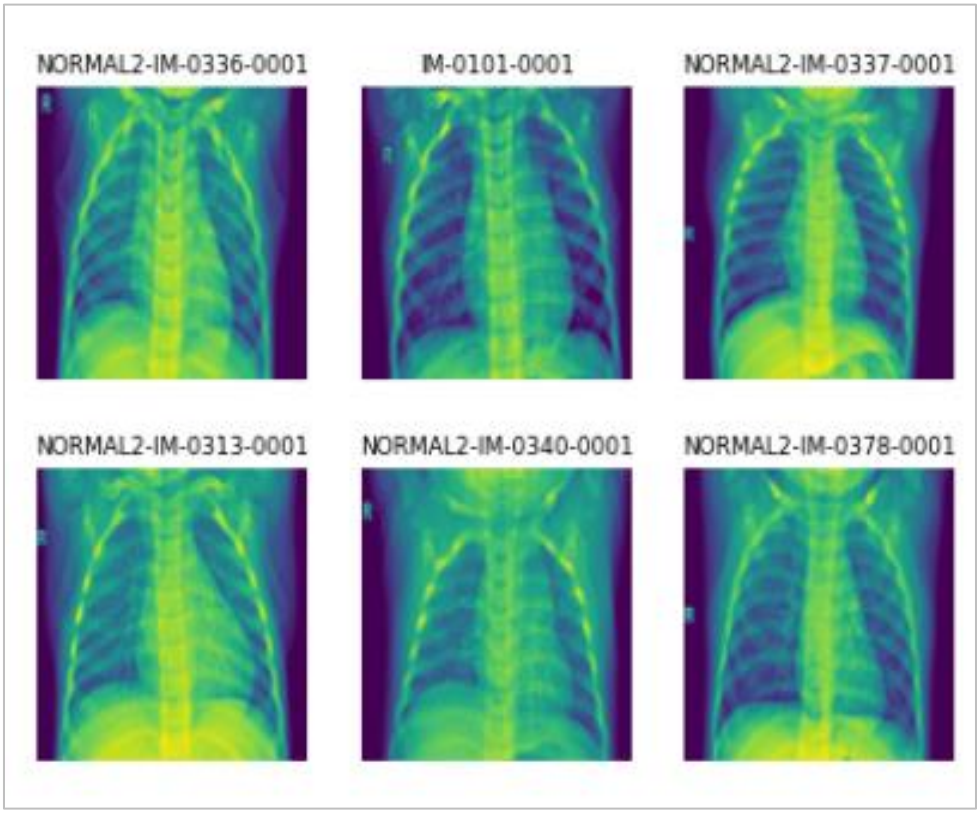


Fig. 3: Representation of Input Data After Pre-Processing

In post-processing, the chest X-ray images have local resolution norms and standardized intensity levels, which increase the anatomical clarity and the consistency with which the images have contrast. This makes it easier to extract robust features and enhances reliability in deep learning-based pneumonia classification in COVID-19 as shown in fig.3. Data augmentation is employed to diversity the dataset and mitigate bias during model training. Examples of techniques that emulate real-world radiography variations to allow deep learning models to derive strong and invariant features to the diagnosis of COVID-19 pneumonia are rotation, shifting, shearing, zooming, horizontal flipping, and intensity rescaling.

Classification Algorithm

CNN: The traditional CNN is used as a reference model in forecasting the pneumonia of COVID-19 by the use of chest X-ray images. It includes a series of stacked convolutional layers, a series of pooling layers that lead to the reduction of spatial features and a fully connected layer that results in the achievement of classification. The CNNs are useful in the capturing of low and mid visual patterns like edges, textures or lung opacities.

Algorithm 1

Input: Preprocessed chest X-ray image $I \in R(H \times W)$

Output: Class label $y \in \{\text{Normal, Pneumonia}\}$

1: Initialize convolutional filters W_c and biases b_c

2: for each convolutional layer l do

3: $F_l = \text{ReLU}(\text{Conv}(I, W_{ci}) + b_{ci})$

4: $Pl = \text{MaxPool}(Fl)$

5: $I \leftarrow Fi$

6: end for

7: Flatten final feature map F

8: Compute fully connected output:

$$O = \text{Softmax}(Wf \cdot F + bf)$$

9: Predict class $y = \text{argmax}(O)$

10: Return y

EfficientNet: EfficientNet, in the given research, will improve the learning of features by effectively capturing delicate radiographic patterns that are linked to COVID-19 pneumonia. Its better designed architecture allows it to be more accurate than conventional CNNs, but with acceptable computational cost. Nevertheless, EfficientNet models are somewhat resource-intensive, and thus may not be applicable in low-resource clinical settings.

Algorithm 2

Input: Preprocessed chest X-ray image $I \in R(H \times W)$

Output: Class label $y \in \{\text{Normal}, \text{Pneumonia}\}$

1: Scale network

2: for each MBConv block i do

3: $Fi = \text{MBConv}(I, k_i, w_i, d_i)$

4: $Fi = \text{Swish}(\text{BatchNorm}(Fi))$

5: $I \leftarrow Fi$

6: end for

7: Apply global average pooling to final feature map

8: Compute output probability:

$$O = \text{Softmax}(W \cdot \text{GAP}(F) + b)$$

9: Predict class $y = \text{argmax}(O)$

10: Return y

Lightweight-MobileNet: MobileNet is efficient when it comes to capturing Discriminative lung features as well as it allows quicker inference and reduces the use of memory in the context of chest X-ray classification. This contributes to its applicability in edge-computations as well as diagnostic systems that can be carried around. Although it is lightweight, MobileNet attains competitive performance with more profound architectures as shown in fig. 4.

Algorithm 3

Input: Pre-processed chest X-ray image $I \in R(H \times W)$

Output: Class label $y \in \{\text{Normal}, \text{Pneumonia}\}$

1: Initialize depthwise and pointwise convolution filters

2: for each depthwise separable block do

3: $Fd = \text{DepthwiseConv}(I)$

4: $Fp = \text{PointwiseConv}(Fd)$

5: $F = \text{ReLU}(\text{BatchNorm}(Fp))$

6: $I \leftarrow F$

7: end for

8: Apply global average pooling

9: Compute class scores:

$$O = \text{Softmax}(W \cdot \text{GAP}(F) + b)$$

10: Predict class $y = \text{argmax}(O)$

11: Return y

Lightweight-EfficientNet: Lightweight EfficientNet is an architecture that is optimized to achieve even lower computational costs by incorporating the advantages of EfficientNet scaling of compounds in addition to architectural optimization. It has good feature representation ability but with minimum parameters and inference

time. This model exhibits optimal performance in recognizing COVID-19 pneumonia by effectively balancing accuracy, memory, and efficiency. Its architecture is highly suitable to scalable and real time clinical diagnostic applications that are resource limited.

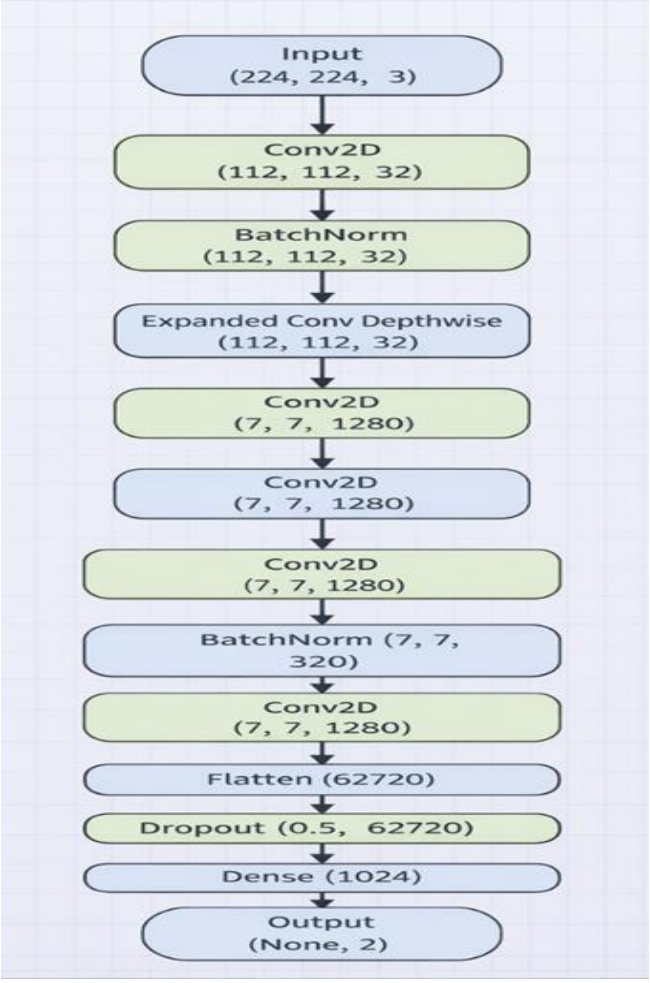


Fig. 4: Architecture of Lightweight Deep Learning Model for Pneumonia Classification

Algorithm 4

Input: Pre-processed chest X-ray image $I \in R(H \times W)$

Output: Class label $y \in \{Normal, Pneumonia\}$

1: Apply optimized compound scaling with reduced parameter constraints

2: for each lightweight MBConv block do

3: $Fi = DepthwiseConv(I)$

4: $Fi = PointwiseConv(Fi)$

5: $Fi = Swish(BatchNorm(Fi))$

6: $I \leftarrow Fi$

7: end for

8: Perform global average pooling

9: Compute prediction:

$$O = Softmax(W \cdot GAP(F) + b)$$

10: Predict class $y = argmax(O)$

11: Return y

Fig. 5 illustrates the EfficientNetB0 classification pipeline, which employs feature extraction, global average pooling, dense layers, and dropout regularization to proficiently learn and accurately identify COVID-19 pneumonia using chest X-ray images in a binary classification framework.

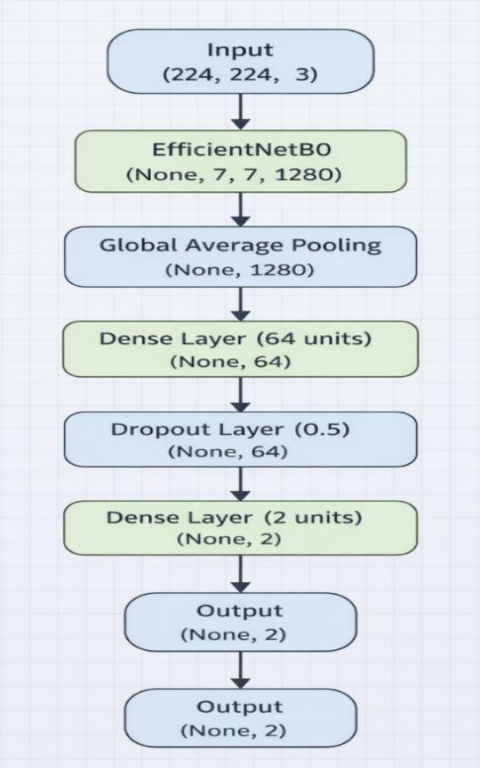


Fig. 5: EfficientNetB0-Based Classification Architecture for COVID-19 Pneumonia Detection

Result And Discussion

The sample on which the exploratory testing was conducted was the Kaggle Chest X-Ray Pneumonia. The dataset was used to construct a training directory, a validation directory, and a test one. The training dictionary was of two classes namely normal and pneumonia. All the pictures of the chest X-ray were resampled and reduced to the 1/255 range after being down sampled to 224 × 224 pixels.

Techniques of data augmentation were used to improve training data, therefore, improving model generalization and reducing overfitting. The functions included image rotation, adjusting width and height, shearing, zooming and flipping horizontally. The data were divided into sets where 80 percent belonged to the training and 20 percent to testing where model selection and evaluation was done using validation data. Four trained deep learning classifiers were used, which were CNN, EfficientNet-B0 and the lightweight MobileNet and the lightweight EfficientNet. The learning rate was 1 x 10-4, and the batch size was 32 to improve the performance of the model using the Adam optimizer. The training was carried out until the early stopping technique because the training would overfit. Performance metrics were used to determine the efficacy of the model as accuracy, precision, recall, and F1-score.

Table 2 gives a comparison between the complexity of the model in terms of trainable and non-trainable parameters. The CNN model has low memory specifications with all the parameters trainable. EfficientNet-B0 is of moderate complexity and the percentage of non-trainable parameters is small. The lightweight MobileNet will have a significantly larger size of the parameter, and the lightweight EfficientNet will have fewer parameters that can be trained, which implies effective reuse of the features and is very well adapted to be deployed in the resource-constrained setting.

Table 2: Trainable and Non-Trainable Parameters Comparison

Model	Total_Param (MB)	Trainable_Param (MB)	Non-Trainable_Param (MB)
CNN	4.7	4.7	0.0
EfficientNet	16.2	16.0	0.2

Lightweight MobileNet	246.4	237.9	8.5
Lightweight EfficientNet	15.8	0.4	15.4

The performance of the CNN model during training and validation is depicted in fig. 6, which spans multiple epochs. The accuracy of training progressively rises and the loss of training is in a steady decline which depicts favorable learning. There are moderate variations in validation accuracy and validation loss is still greater than training loss, indicating that there is little generalization ability and there is slight overfitting in the default CNN architecture. Fig. 7 illustrates that the EfficientNet model exhibits robust feature learning, evidenced by high and stable training accuracy alongside minimal training loss. Validation accuracy increases in general but has some observable oscillations and there is also variating validation loss. These trends mean that it has better representational power than CNN, but it is sensitive to changes in data at the time of validation.

Fig. 8 shows that the Lightweight MobileNetV2 model converges rapidly, and the training accuracy increases rapidly, and the training loss drops to a minimum. The accuracy of validation also varies with the epoch, whereas the loss of validation is also varied, indicating the lightness of the model. Although it is less complex, the model still has competitive performance as well as effective learning behavior.

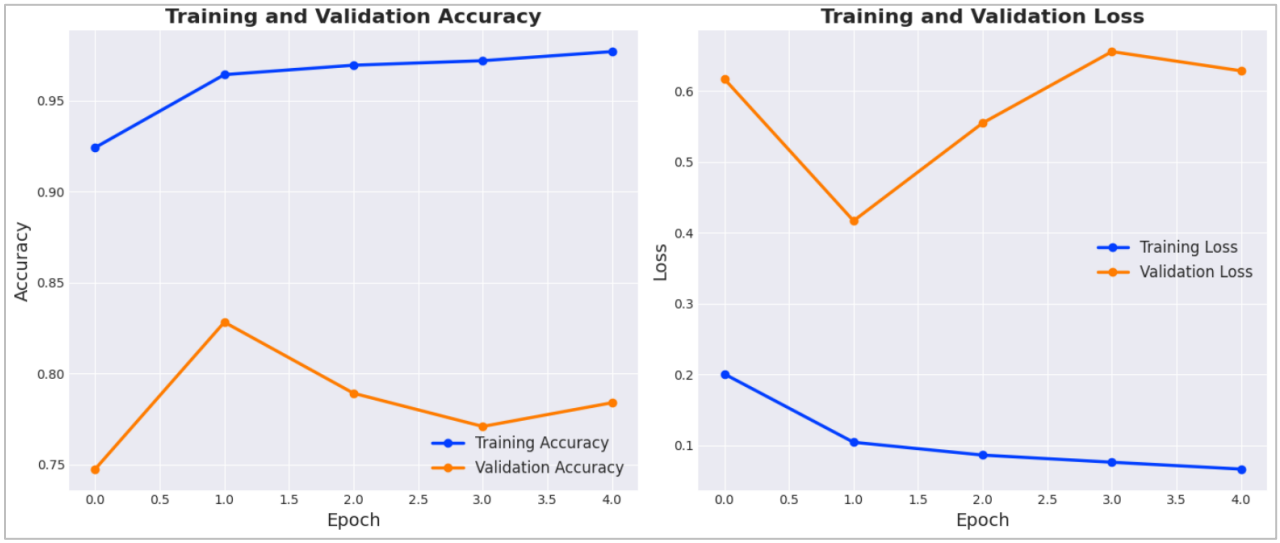


Fig. 6: Accuracy and Loss Curve for CNN model

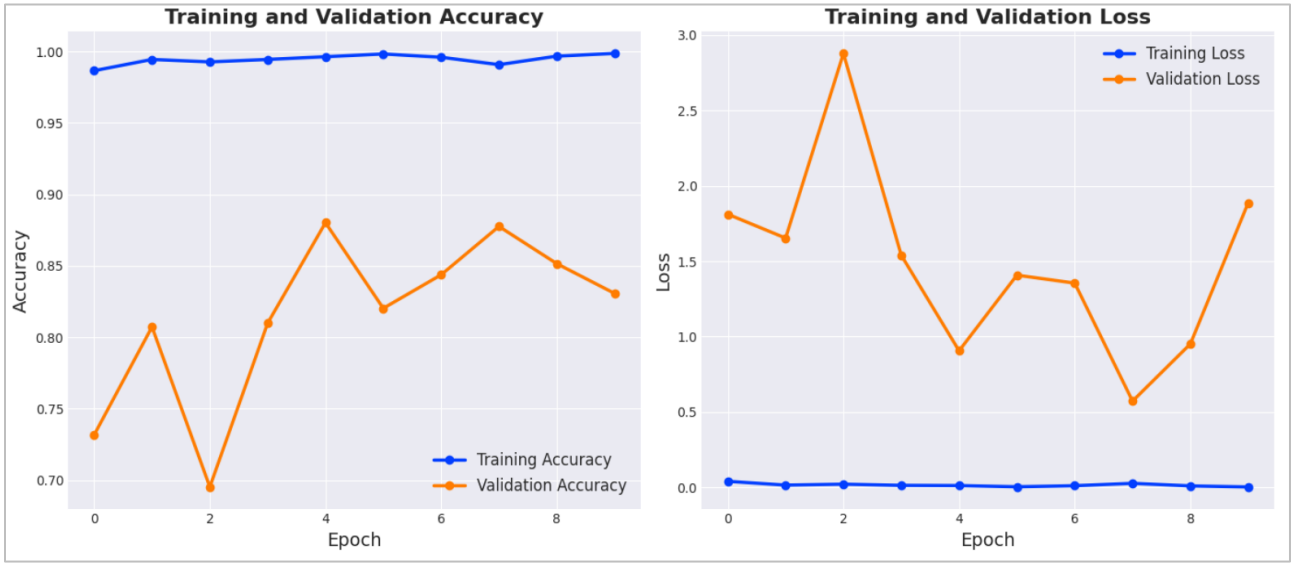


Fig. 7: Accuracy and Loss Curve for EfficientNet Model



Fig. 8: Model Accuracy and Loss Curve for Lightweight-MobileNetV2



Fig. 9: Accuracy and Loss Curve for Lightweight-EfficientNet Model

The model of Lightweight EfficientNet, as shown in fig. 9, has a high training accuracy and a steady reducing training loss. There is a high accuracy of validation and low loss of validation. These trends show better performance on generalization, balance learning, and optimization, and it is suitable in real-time and reliable COVID-19 pneumonia classification tasks.

Table 3: Performance Comparison of Deep Learning Algorithms

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN	86.4	85.2	84.1	85.0
EfficientNet	88.6	90.3	85.4	86.2
Lightweight MobileNet	90.2	92.1	87.6	89.3
Lightweight EfficientNet	92.5	92.4	90.1	90.2

Table 3 can be found as an in-depth evaluation of the performance of four deep learning algorithms evaluated to diagnose COVID-19 pneumonia on the basis of the chest X-ray imagery. The CNN baseline model attains an accuracy of 86.4%, with equalized precision, recall, and F1-score values of 85, signifying sufficient classification capacity but constrained discriminative efficacy on intricate pulmonary patterns. The EfficientNet model is the most effective, and its accuracy is 88.6% with a significant precision of 90.3 which proves the increased effectiveness at recognizing patients with pneumonia. However, it has a relatively low recall rate of only 85.4 which indicates that it does not in some instances detect pneumonia.

Lightweight mobile net model is the enhanced version of the former model, whose accuracy and precision stand at 90.2 and 92.1 respectively, which implies that it is a predictive model with high confidence. Its sensitivity to the pneumonia cases is greater than CNN and EfficientNet (87.6% vs. 83.5%), its F1-score is significantly increased (89.3% vs. 83.6%). This is because, these results suggest that lightweight architectures are capable of attaining high diagnostic performance with reduced computation complexity. The Lightweight EfficientNet model has superior performance across all evaluation criteria, with an accuracy of 92.5, precision of 92.4, recall of 90.1, and an F1-score of 90.2. The balance between accuracy and the level of recall is important in clinical diagnosis, as it lessens the false positives as well as false negatives.

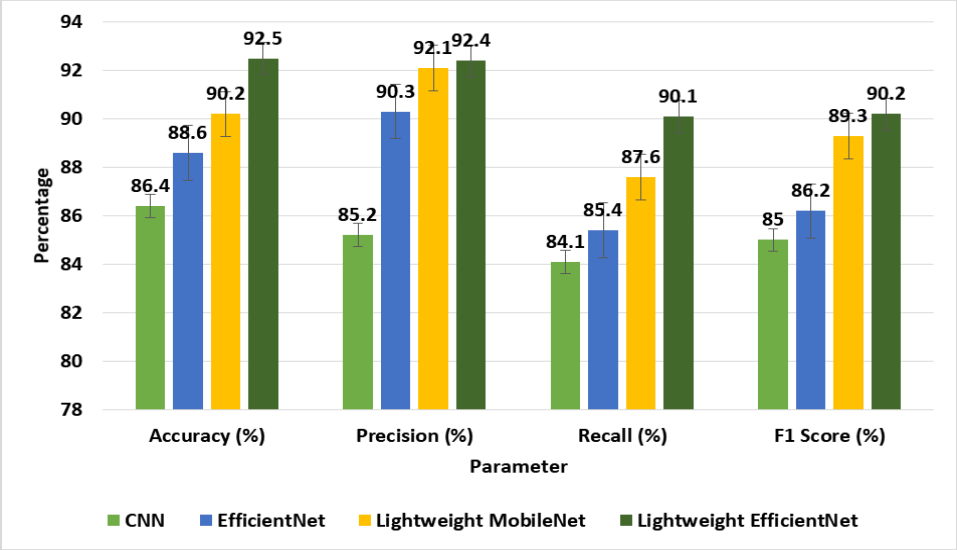
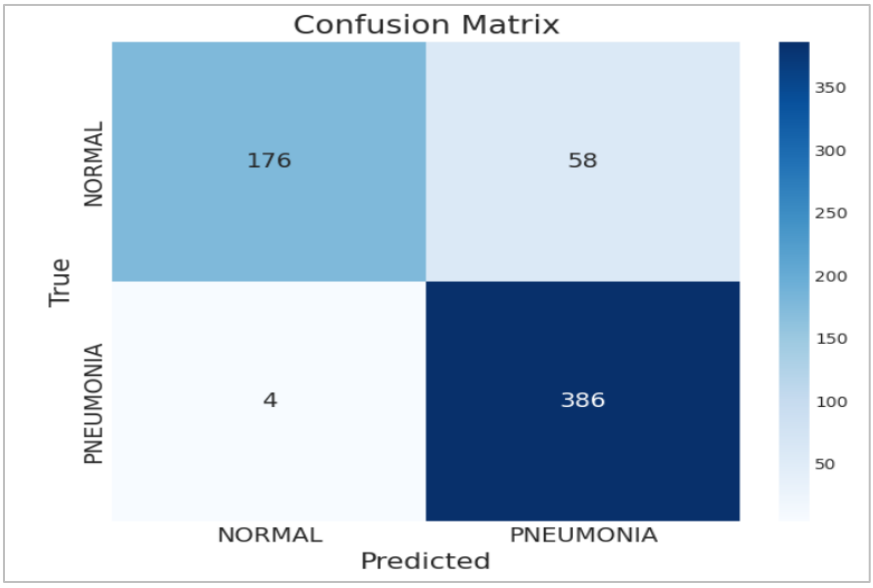
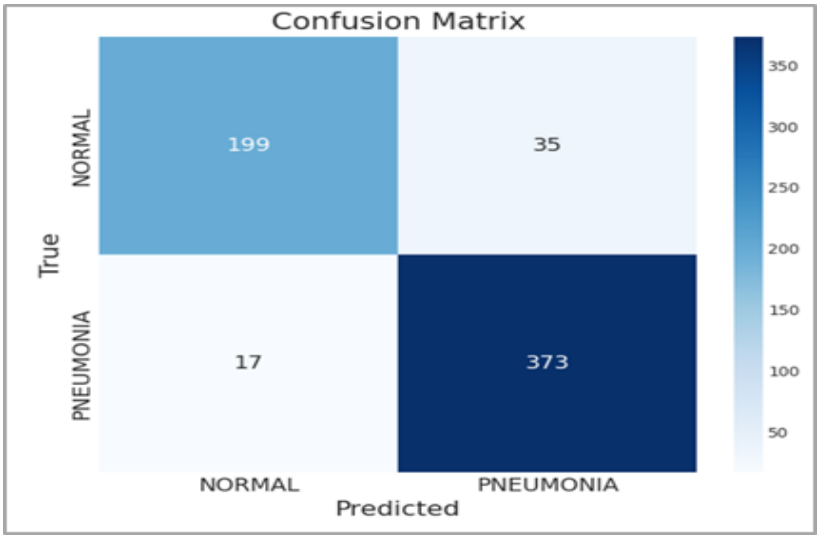


Fig. 10: Comparative Performance Analysis of Deep Learning Models for COVID-19 Pneumonia Detection

Overall, these results support the statement that optimized lightweight deep learning models represent an acceptable tradeoff between accuracy, efficiency, and reliability and can be used in real-world applications in screening COVID-19 pneumonia. The accuracy, precision, recall, F1-score of the assessed models are shown in fig. 10, it is clear that the lightweight EfficientNet is always better than the rest, as it has a higher diagnostic reliability and equal efficacy in identifying COVID-19 pneumonia using chest X-ray images.



(a)



(b)

Fig. 11: Confusion Matrix of (a) Lightweight-MobileNet Model (b) Lightweight- EfficientNet Model

Fig.11 indicates the confusion matrices of the lightweight MobileNet and lightweight EfficientNet models that indicate their classification performances when used to identify cases of COVID-19 pneumonia using the chest X-ray. Fig. 11(a) shows that the lightweight MobileNet model has a high sensitivity to pneumonia, distinguishing most of the cases with significantly large number of true positives and very small number of false negatives. There is however no attack of high volume of normal cases falsely diagnosed as pneumonia which is a level of reduced specificity. However, the model is good in discriminating and is computationally efficient hence can be used in rapid screening. As shown in fig. 11(b), the confusion matrix of the lightweight EfficientNet model has a better sensitivity-specificity ratio. The number of correctly identified normal and pneumonia cases is higher, and false positive and false negatives are lower than the MobileNet model. This implies a higher generalization rate and more valid decision frontiers. The decreased error of normal cases is especially significant in clinical cases to reduce excessive follow-up tests. Altogether, the confusion matrix analysis proves that lightweight EfficientNet provides more consistent and accurate predictions, which would prove its usefulness as a strong deep learning solution to pneumonia detection.

Table 4: Performance Comparison of Deep Learning Models Using Five Evaluation Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)
CNN	86.4	85.2	84.1	85.0	87.1
EfficientNet	88.6	90.3	85.4	86.2	89.5
Lightweight MobileNet	90.2	92.1	87.6	89.3	91.0
Lightweight EfficientNet	92.5	92.4	90.1	90.2	93.2

Table 4 shows the comparison of the performance of the tested models of deep learning based on five major metrics, namely accuracy, precision, recall, F1-score, and specificity. Lightweight EfficientNet was the most successful model with the overall result of 92.5 percent, 92.4 percent Precision, 90.1 percent Recall, 90.2 percent F 1 score, and 93.2 percent specificity, which implies the good and balanced classification. Lightweight MobileNet also gave a competitive performance with 90.2 percent accuracy and 89.3 percent F1-score, which validates the efficacy of lightweight structures in efficient medical image examination. EfficientNet performed better than the baseline CNN on most measures, especially, precision and specificity and demonstrated its better discriminating capacity over pneumonia-related features. On the contrary, the CNN model had the lowest score in all metrics, indicating its relatively poor generalization capacity. In general, the findings indicate that lightweight transfer learning models are a more suitable compromise between diagnostic accuracy and computing efficiency to be used in practice in pneumonia detection by examining chest X-ray images.

Ablation Study

- Backbone architecture comparison: The comparison study was performed by comparing CNN, EfficientNet, Lightweight MobileNet and Lightweight EfficientNet on the same preprocessing and training conditions to investigate the impact of network architecture on classification performance.
- Effect of data augmentation: The effect of augmentation was evaluated by training the most successful model with and without augmentation processes like rotation, shifting, zooming and flipping and it was discovered that augmentation enhanced generalization and decreased overfitting.
- Lightweight optimization effect: To assess the impact of lightweight architecture optimization, an independent comparison of standard EfficientNet and Lightweight EfficientNet was conducted to determine that the reduction of model complexity did not reduce or did not even decrease diagnostic performance.

Conclusion

This work comparatively analyzes deep learning algorithms for detecting COVID-19 pneumonia in chest X-ray pictures, addressing the necessity for diagnostic support systems to be accurate, efficient, and feasible. This was done systematically in which a clinically curated pediatric X-ray dataset was pre-processed to enhance images, augment data, split data equally between training and testing, and maintain all models under comparable experimental conditions. As results of the experiments demonstrated, the lightweight architectures are much more effective than the traditional CNNs having a complexity of calculations that is less. The CNN baseline achieved a fair performance that was not too much generalization and overfitting. EfficientNet was more precise and denoted more characteristics yet there was instability during validation. Lightweight MobileNet has proven to be convergent in a shorter time and comparable accuracy levels with its competitors, hence the suitability of this learning model in the implementation of real time screening cases. The Lightweight EfficientNet model exhibited superior overall performance, achieving the maximum accuracy (92.5%), precision (92.4%), recall (90.1%), and F1-score (90.2), alongside a consistent training pattern and a balanced confusion matrix. The analysis of the accuracy and loss curves, in conjunction with the confusion matrix, revealed the higher generalization capabilities of the Lightweight EfficientNet model. The evaluation of false positives and false negatives inside the confusion matrix is crucial for clinical reliability. The result that is justified by the comparative performance is that light-weight deep learning models are optimized to provide a reasonable trade-off between the diagnostic and implementation performance. This publication is strong because Lightweight EfficientNet is a viable and powerful platform of the COVID-19 pneumonia detection using the chest X-ray imaging. The results indicate that it might be incorporated into the paradigm of the real-world clinical practice, particularly in the healthcare institutions with low resources, and has a strong basis on the future studies in scalable medical image-based detecting diseases.

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