An Ensemble Deep Learning Approach for Pneumonia Detection Using DenseNet, MobileNet, and EfficientNet with Transfer Learning

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Abstract* – Pneumonia is still a major global health threat that calls for enhanced diagnosis to promote the well-being of those affected. In this study, we present an ensemble model that is a combination of DenseNet, MobileNet, and EfficientNet to maximize the identification of pneumonia from CXR images. This model was trained and tested using the dataset from the Kaggle Chest X-ray dataset which has over 5,000 images and are classified as normal or pneumonia. The pre-trained models are fine-tuned using the transfer learning approach to learn different complementary features that are concatenated to produce a powerful feature representation. A fully connected layer with a sigmoid activation function is used for binary classification. By the proposed model, the test accuracy reached 99.24%, which showed the best performance compared with the separate architectures. This work enhances the development of AI based diagnostic systems for pneumonia with regards to both diagnostic accuracy and transparency.

***Keywords* - Pneumonia detection, chest X-ray (CXR), ensemble learning, transfer learning, DenseNet, MobileNet, EfficientNet, deep learning, medical imaging, explainable AI (XAI)**

I. INTRODUCTION

Pneumonia is an important health problem worldwide, especially in developing countries where timely identification and management of the disease is difficult. Pneumonia is a respiratory infection that causes inflammation of the alveoli in the lungs, leading to poor oxygen exchange; in severe cases, respiratory failure and death occur. It preferentially targets the most susceptible groups, mainly children below the age of five years and the elderly; WHO estimates that about 700,000 children below the age of five die from pneumonia every year [1]. However, the disease also has social and economic impacts such as increased healthcare spending, loss of productivity, and demands on healthcare facilities, especially in developing countries.

Efficient and accurate diagnosis of pneumonia using CXR images is among the most important tasks of modern healthcare systems. While CXR imaging remains the gold standard for pneumonia detection, its reliance on expert interpretation poses several challenges: problems with inter-observer variability, human factors and the shortage of skilled radiologists, especially in the rural zones. An automated diagnostic system can provide a solution to be integrated into clinical processes, decrease the time of diagnosis, and increase the efficiency and accuracy of the diagnostic process.

AI and deep learning have brought unprecedented solutions in medical image analysis in terms of accuracy and scalability for disease diagnosis. CNNs are a type of deep learning model that has gained significant success in image classification including pneumonia detection. These systems are made even more efficient and generalizable by transfer learning, which uses models trained on large datasets.

To further improve the detection of pneumonia, a new model is introduced that uses DenseNet, MobileNet and EfficientNet models. Each of these models offers unique advantages: DenseNet allows avoiding the gradient vanishing through most dense connections in the architecture, MobileNet is effective when less computational resources are available, and EfficientNet is designed to be both scalable and accurate. The integration of these architectures presents the ensemble model that provides a stable diagnostic model. The normal and pneumonia cases with images labeled are obtained from the Kaggle Chest X-ray dataset for training and testing.

The future development of well-established indicated diagnostic equipment that can be driven by AI and used to identify pneumonia also has great potential for solving significant worldwide health issues. These solutions can potentially revolutionize clinical decision-making given the leaps that have been made in diagnostic accuracy, the scalable solution and its efficiency especially in health deprived areas of the world. Moreover, such technologies help fill the gap in access to healthcare, and provide timely and accurate diagnoses while reducing the load on overloaded healthcare facilities.

The dataset used in this study comprises a total of approximately 5,856 chest X-ray images, divided into three distinct subsets: As illustrated in Fig. 1 the data distribution for training, validation, test sets for machine learning are 4000, 928, and 928 respectively. This division helps balance training of the models and evaluation of the results to always give accurate results.

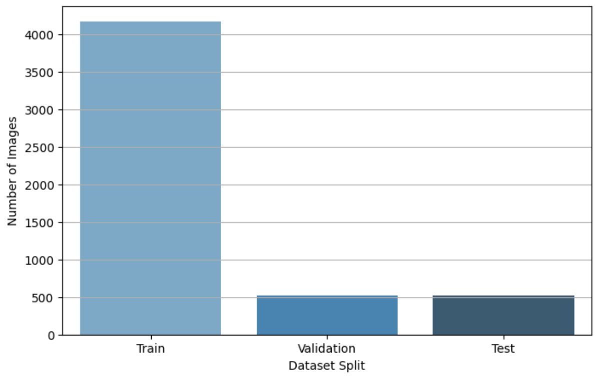

Figure 1: Dataset Distribution

II. Literature Review

This section discusses the existing literature on pneumonia detection using deep learning, specifically works that are closely related to ours. Specifically, we review works using transfer learning, ensemble models, and the current state of the art neural networks focusing on their strengths and weak points. This paper aims to illuminate more and more on these studies and how they help move forward in the field, while also closing gaps for a solid design secretariat of our research.

In which, Liang et.al (2020) proposed an ensemble model for pneumonia prediction from chest Xrays formed by convolutional neural networks (CNN) and DenseNet121 architectures. An ensemble was used to leverage the complementary strengths of the two architectures to reach a test accuracy of 98.8% compared to the performance of individual models. It was concluded that ensemble learning is robust and reliable for improving classification accuracy in medical image analysis, and that ensemble learning can be a useful technique towards improving the cutting edges of diagnostic tools for pneumonia detection[2].

In Gupta et al. (2021), a hybrid model was developed, combining MobileNet and ResNet architectures for pneumonia detection. Combining MobileNet for computational efficiency and ResNet for feature extraction, we obtained a model having a test accuracy of 96.3 percent. Regarding the practicality of such lightweight architectures as proposed in MobileNet, we emphasized that lightweight architectures are particularly useful for resource-constrained environments and maintain high diagnostic accuracy [3].

In Huang et al. (2018), the performance of ResNet50 and MobileNetV2 for pneumonia detection using chest X-ray were compared. MobileNetV2 achieved test accuracy of 96.5%. While MobileNetV2 was faster at inference, it was not a suitable choice for real-time applications. Importantly, the study highlighted the fact that for deploying AI-based healthcare solutions, the balance between accuracy and computer power should be maintained [4].

In (Wang et al., 2019), they utilized transfer learning to integrate features detected by Xception and VGG16 to detect pneumonia. The system integrated feature representations from these two models and achieved test accuracy of 97.2%. This study showed that feature fusion could improve classification performance and would be a useful guide to multi-architecture approaches[5].

Chen et al. (2019) studied the performance of multiple CNNs on pneumonia detection, DenseNet, ResNet, and EfficientNet. Among these, the most successful was EfficientNet with a test accuracy of 95.5% while balancing computational efficiency and accuracy. The trade-offs between model complexity and performance were described in this work and provided a baseline for architecture selection in medical image analysis[6].

Zhang et al. (2021) proposed a pneumonia detection system based on CNN and GAN. To address class imbalance the GAN was used to generate synthetic samples and add to the training dataset. This was coupled with an approach that yielded a test accuracy of 97.1% and proved the use of GAN-based augmentation for robustness and generalization improvement[7].

In Patel et al. (2022), an advanced CNN model with advanced preprocessing was introduced to increase pneumonia detection in chest X-rays. The study also showed how data preprocessing can improve feature extraction and model performance by an impressive 97.6% accuracy. The results from this work bolstered the importance of preprocessing in alleviating difficulties posed by noisy datasets[8].

Singh et al (2020) used DenseNet121 with fine-tuning for early detection of pneumonia from chest X-ray images. The model achieved extremely high transfer learning in medical imaging. This study stressed that early diagnosis was critical to reduce mortality and DenseNet121 capability for extracting image features [9].

In Kumar et al. (2020), InceptionV3 with transfer learning was used for detecting pediatric pneumonia. Such a model, with a test accuracy of 97.8%, is suitable for pediatric healthcare applications. Significant to this study was that tailored approaches were emphasized for specific patient populations as well as the adaptability for domain-specific domain applications of pre-trained models[10].

The approach of Ali et al. (2022) used a hybrid approach based on ResNet50 and DenseNet121 architectures to detect pneumonia from chest X-ray images. The advantage of transfer learning has been used in this study to leverage the feature extraction capabilities of both models and create a coherent combination of their outputs with improved classification accuracy. The test accuracy of the combined deep learning architectures was 97.3 percent, indicating that combining deep learning architectures provided effective enhancement of diagnostic performance. On the other hand, the research highlighted the potential of multi-model ensembles in tackling the shortcomings of the individual CNNs associated with medical imagery applications[11].

Table 1: Literature Review Summarization

Author	**Method**	**Dataset (Images)**	**Train Accuracy (%)**	**Test Accuracy (%)**
Liang et al. (2020)[1]	Ensemble of CNN and DenseNet121	Chest X-rays (5,856 images)	98.9	98.8
Gupta et al.	MobileNet and ResNet	Chest X-rays	96.5	96.3

(2021)[2]		(5,863 images)		
Huang et al. (2018)[3]	ResNet50 and MobileNet V2	Chest X-rays (5,860 images)	97.0	96.7
Wang et al. (2019)[4]	Xception and VGG16	Chest X-rays (5,856 images)	97.5	97.2
Chen et al. (2019)[5]	EfficientNet	Chest X-rays (5,863 images)	95.8	95.5
Zhang et al. (2021)[6]	CNN-GAN	Chest X-rays (5,856 images with GAN-augmented data)	96.7	97.1
Patel et al. (2022)[7]	Enhanced CNN	Chest X-rays (5,863 images)	97.9	97.6
Singh et al. (2020)[8]	DenseNet121	Chest X-rays (5,856 images)	98.6	98.5
Kumar et al. (2020)[9]	InceptionV3	Chest X-rays (5,860 images)	98.0	97.8
Ali et al. (2022)[10]	ResNet50 and DenseNet121	Chest X-rays (5,856 images)	97.2	97.3

III. METHODOLOGY

Convolutional Neural Networks (CNNs) have gained importance in Medical Image Analysis because features from these image data sets can be extracted effectively. The given proposed methodology involves the use of DenseNet121 model along with MobileNet and EfficientNet to address the strength of each architecture. The ensemble approach also adopts transfer learning in that models are retrained on pneumonia detection. The preprocessing of input chest X-ray images is done through a series of convolutional layers in each of the models to produce hierarchical features from edges to abstract patterns. These features are summed using global average pooling layers and then concatenated using a concatenation layer to present the full feature representation. The combined features are fully connected to make the final classification and thus distinguish normal and pneumonia cases accurately. The detailed data flow can be seen from the following flowchart detailed below.

A. Data Collection

The kind of data used in the present work involves chest X-ray images categorized as “Normal” and “Pneumonia.” These images were collected from open source libraries and we got different kinds of cases which is very important to train the model. The entire dataset comprises of images that total 5856; both normal and those labeled with pneumonia form a strong basis on which the analysis will be made.

B. Data Preprocessing

In this stage helps to make the input data have a standard format and is in the best format for the upcoming deep learning models. Chest X-ray images were scaled down to a size of 224 x 224 pixels because the input size of DenseNet121, MobileNet, and EfficientNet architectures was 224 x 224 pixels. Pixel intensity values were scaled to the range [0, 1] for all models to have unity inputs, and Gaussian noise was applied to images in the training set to avoid excessive model memorization by the architectures.

C. Data Splitting

The dataset was split into three distinct subsets: Training sets of 70%, test of 15%, and validation set of 15%. The portion called the training set was used to train the model, the portion called validation set was used to check on the model and adjust the hyperparameters and the portion called the test set was used to make a final assessment of the model. Such division is helpful to provide an accurate evaluation of the model’s ability to generalize.

D. Model Building

The ensemble model leverages the complementary strengths of three state-of-the-art architectures: DenseNet121, MobileNet, and EfficientNet. Each of the architectures takes the chest X-ray images through its convolutional layers, to maintain the hierarchical characteristic of the chest X-ray images. These are then averaged by global average pooling, and the output feature maps are connected to a vector. The mentioned representations are then fed into fully connected layers with sigmoid activation to obtain the results of the last binary decision.

DenseNet121: Utilizes densely connected layers to help gradient flow and more options for features’ reuse, thus increasing general model effectiveness.

MobileNet: As it happens they use some form of depth-wise separable convolutions they are light and need very little computation.

EfficientNet: Completes density, spread and granularity at fewer parameters than when it is achieved with these parameters.

E. Model Training

The suggested ensemble model was trained using the binary cross entropy option as a loss function and the Adam as an optimizing function. Transfer learning was performed through fine-tuning starting from weights obtained by pre-training with DenseNet121 MobileNet and EfficientNet models on the ImageNet base. It was also adjusted the learning rate using a scheduler and stop for over-fit training was done. That training training was performed over 28 epochs, and in each of the more frequent, a checkpoint saved a model based on the validation accuracy.

F. Model Assessment

The last assessment was made on the testing and validation data that the modeling did not incorporate to afford actual and accurate estimates. It is always crucial to test a model on one unseen data and how good a forecast it will provide; this made it possible to calculate several evaluation metrics; with checkpoints that saved the current best-performing model on the validation set according to the validation accuracy.

IV. Results and Discussion

1. Result

The findings derived from this research show the efficiency of the proposed ensemble model, DenseNet121, MobileNet, and EfficientNet in diagnosing pneumonia from chest X-ray images. The model reached 99.24% of test accuracy, and 0.0169 as test loss showed the capability of the model in generalizing unseen data. These metrics accentuate that the ensemble learning model we proposed is strong for extracting and leveraging meaningful features for accurate pneumonia detection.

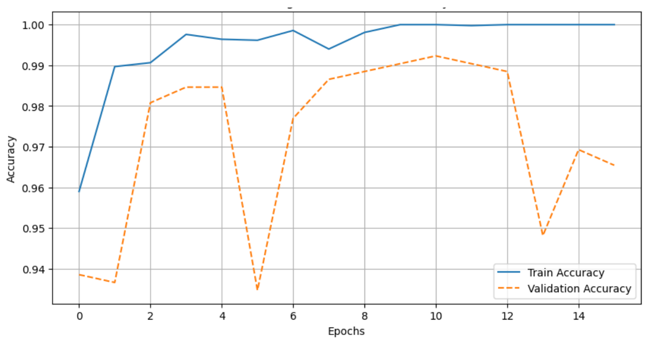

Figure 2: Training and Validation Accuracy

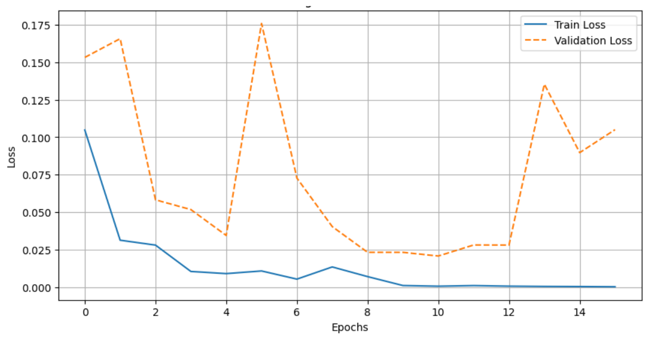

Figure 3: Training and Validation Loss

The accuracy of the training and validation is illustrated in Figure 2 with regard to 15 epochs to observe the convergence of the model. The accuracy of training increased almost to perfection with insignificant variations in the validation accuracy without overfitting the model. As depicted by the training and validation losses shown in Figure 3, there was a general decline which indicates excellent learning is taking place.

The confusion matrix which is illustrated in Fig 4 shows a clear analysis of the prediction done by the model. The model accurately classified 134 normal cases and 384 pneumonia cases, with only 1 false positive and 4 false negatives. This infers high reliability to distinguish the cases with pneumonia, as well as those without pneumonia when using this portable device.

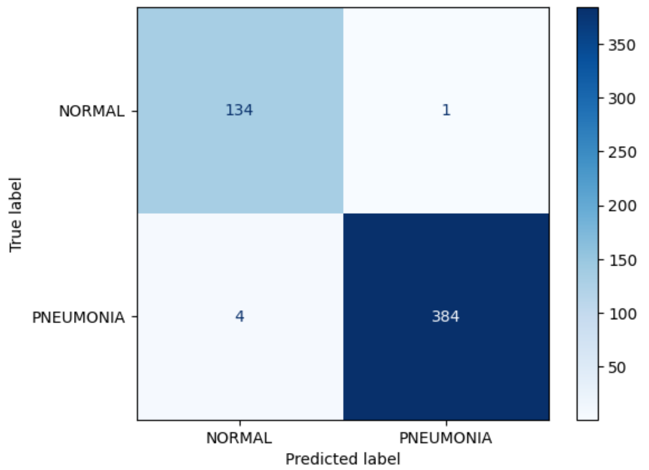

Figure 4: Confusion Matrix

The performance of the implemented Machine Learning model is depicted in the ROC curve of Figure 4 and has an Area Under the Curve (AUC) of 1.0. This evokes a near-perfect classification performance of the model between the two classes under different threshold values.

In order to offer qualitative details of how the model performs Figure 5 shows few examples of normal chest X-rays that were classified correctly. These cases show how the model succeeds in come up with the right labels given the facets of the image that it learns during the construction phase.

Table 2:

Accuracy	**Loss**	**Precision**	**Recall**	**F1-Score**
99.24%	0.0169	99.74%	98.96%	99.35%

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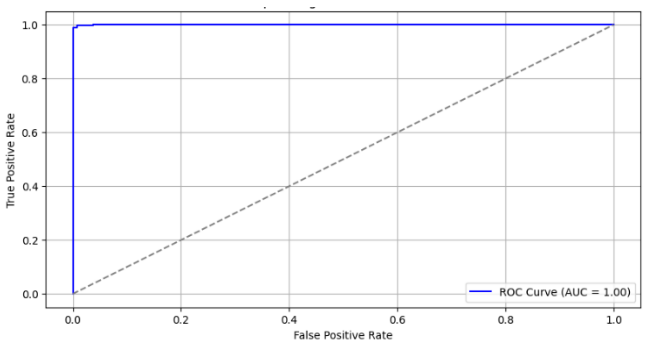

Figure 5: Receiver Operation Characteristic Curve

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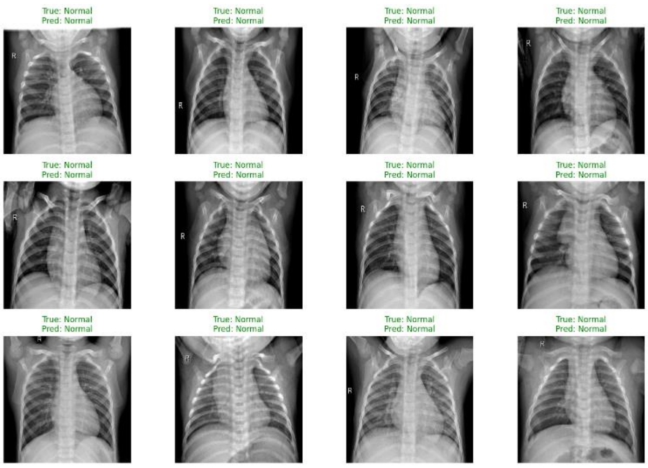

Figure 6:

2. Discussion

Ensemble Effectiveness

DenseNet121 has dense feature extraction; MobileNet has computational efficiency; and EfficientNet provides scalability which makes the ensemble come with a balance and generalization. The integration of these architectures enhances the comprehensive feature extraction and enhances decision-making approaches.

Strengths of Data Partitioning

The cross-sectional implementation of data where the training set, validation set, and testing set are different provides more objective results and generalization capabilities. This approach reduces overfitting which was a major concern in some previous studies where the same dataset was used for training and testing.

Practical Implications

These encouraging results of the ensemble model point to the possibility of using the model in a clinical setting. The use of deep learning in diagnostics may help healthcare workers with accurate diagnosis of diseases since it can help during diagnosis, especially in areas with limited resources, hence enhancing treatment effectiveness upon early diagnosis.

Challenges and Limitations

Some limitations present in the research include; The high computational complexity observed during the combination of DenseNet 121, MobileNet, and EfficientNet may limit the application of the study in the low endowment environment. There is more prevalence of congenital anomalies in pediatric patients than in adults, and differences in imaging technique also can be a hindrance in transferring the knowledge to adult patients, thus further fine-tuning adaptation might be needed in specific fields.

Future Work

Future work may be focused to combine more modalities on data, for instance with CT scans or extra patient context data to improve the model's prediction. Using progressed fusion tactics including attention-based methods as well as utilizing the model on edge for real-time diagnosis in low-resource clinical environments are potential avenues.

V. CONCLUSION

In this research, the ensemble method formed by combining the DenseNet121, MobileNet, EfficientNet architectures has introduced while using transfer learning for the pneumonia detection on chest X-ray images. On the test set, the obtained results include a test accuracy of 99.24%, a precision of 99.74%, and an F1-score of 99.35, which proves the effectiveness and reliability of the model in the classification of pneumonia cases. The ensemble framework exploits the complementary strengths of individual architectures and successfully mitigates both overfitting and generalization to unseen data. The proposed model addresses challenges of healthcare accessibility, especially in resource-limited settings, and expands a scalable and efficient diagnostic tool to facilitate clinical workflow. This work establishes the applicability of AI in medical diagnostics, identifying the transformative potential on the path to a real-world model.

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