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Pulmo Scan: A Deep Learning Framework for Pneumonia Detection using X-Ray Images

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***Abstract:** Pneumonia is an acute respiratory infection of the lung that must be identified at its early stages to keep mortality rates to a minimum, especially in Wireless Body Area Networks (WBAN). Traditional diagnosing methods, i.e., manual interpretation of X-rays, are time-consuming and prone to human errors. The existing models are plagued by generalizability issues, dataset imbalance, and a high false-detection rate, which complicate pneumonia classification. To address these challenges, we propose a CNN-based model that leverages transfer learning to improve detection accuracy. The model consists of three convolutional layers, dropout regularisation, the Adam optimiser, and robust data augmentation methods to learn improved features and prevent overfitting. We trained the model on the Chest X-ray dataset (NORMAL vs. PNEUMONIA) containing 5,863 images. We achieved enhanced accuracy across five state-of-the-art models in our experiments, with higher precision, recall, and F1 Scores. Additionally, the model generalises well by leveraging diverse preprocessing techniques, including image resizing, normalisation, and various forms of augmentation. Compared with existing architectures such as VGG-16, ResNet50, and InceptionV3, the model demonstrated improved robustness and classification accuracy. This research facilitates the development of a solid deep learning framework for detecting pneumonia to be incorporated into real-time medical software.*

***Keywords:** Pneumonia Detection, CNN, Transfer Learning, Chest X-ray, Data Augmentation, Wireless Body Area Networks*

Nomenclature:

DL-Deep Learning
AI-Artificial Intelligence
CNNs-Convolutional Neural Networks
RNN-Recurrent Neural Networks
WBAN: Wireless Body Area Networks
AP-Anterior-Posterior
PA-Posterior-Anterior
MLP: Multilayer Perceptron
k-NN: k-Nearest Neighbours
SMOTE: Synthetic Minority Over-Sampling Technique
CXR: Chest X-ray
RNNs: Recurrent Neural Networks
PA: Posterior-Anterior
MDR: Multidrug-resistant
RBPs: Receptor-Binding Proteins
ANN: Artificial Neural Network

I. INTRODUCTION

Deep Learning (DL) is a branch of Artificial Intelligence (AI) that uses many-layered neural networks to learn from large datasets and identify patterns. DL has advanced many fields, including medical imaging, where it has improved diagnoses. DL models of medical imaging evaluate complex patterns seen on medical scans, free of human error, and contribute to disease diagnosis. An example of deep learning in medicine is the detection of pneumonia from chest X-ray images. Pneumonia (fig. 2) is a lung infection that occurs in the air sacs and can lead to more serious complications if left undiagnosed for a long time. Diagnosing pneumonia using traditional methods is confrontational and relies heavily on the viewer's expertise. In this model, humans may simply become tired or make a mistake, and that mistake can even be life-or-death for a patient.

[Fig.1: Normal]

DL models simplify this step and should significantly increase hospital efficiency. Using pre-trained models and convolutional neural networks (CNNs),

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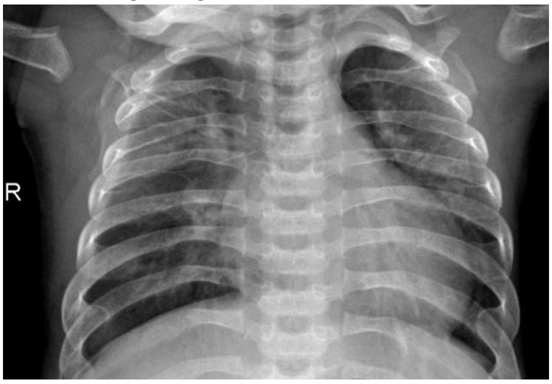
researchers have developed a systematic approach to obtain highly efficient algorithms for pneumonia detection, achieving high recall and very accurate results while minimising errors. In addition to pneumonia detection, other applications of DL in medical imaging include tumour classification, organ segmentation, and disease classification.



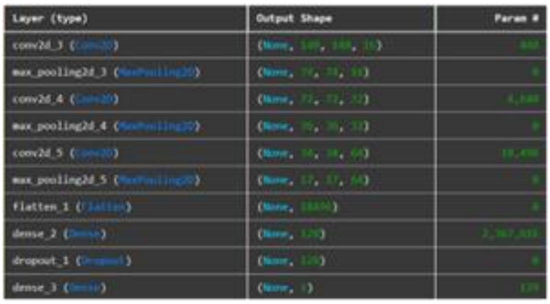
[Fig.2: Pneumonia]

Progression. Architectures such as VGG-16, ResNet, and EfficientNet have been well-suited for detecting and identifying abnormalities in medical images, making deep learning an indispensable tool in contemporary medical research.

A. Deep Learning Models and Architectural Overview

i. *Deep Learning Models in Pneumonia Detection:* Pneumonia diagnosis through deep learning models usually involves Convolutional Neural Networks (CNNs) that are geared to work with imaging data. CNNs learn spatial hierarchies of features from X-ray images, allowing the models to learn features conducive to pneumonia classification. Some widely used architectures that are often used for pneumonia detection:

- Numerous convolutional and pooling layers within the spoke CNN architectures.
- Pre-trained models such as VGG-16, ResNet-50, and InceptionV3 transfer learned features from big data to medical image tasks.
- Hybrid models that combine CNNs with Recurrent Neural Networks (RNNs) to learn spatial and sequential patterns from image data.

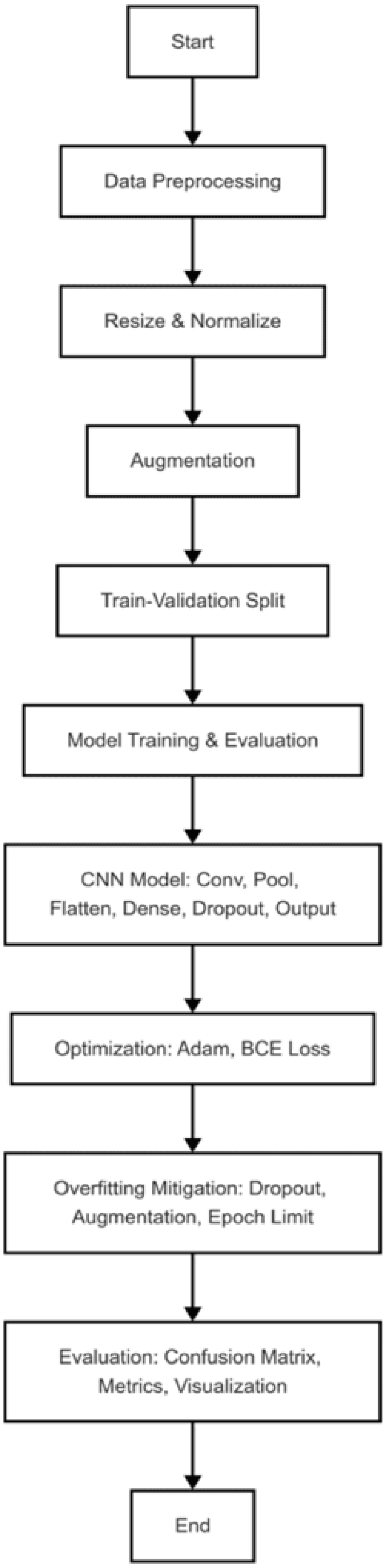


Layer (type)	Output Shape	Param #
conv2d_3 ([illegible])	(None, [illegible])	[illegible]
max_pooling2d_3 ([illegible])	(None, [illegible])	0
conv2d_4 ([illegible])	(None, [illegible])	[illegible]
max_pooling2d_4 ([illegible])	(None, [illegible])	0
conv2d_5 ([illegible])	(None, [illegible])	[illegible]
max_pooling2d_5 ([illegible])	(None, [illegible])	0
flatten_1 ([illegible])	(None, [illegible])	0
dense_2 ([illegible])	(None, [illegible])	[illegible]
dropout_1 ([illegible])	(None, [illegible])	0
dense_3 ([illegible])	(None, [illegible])	[illegible]

[Fig.3: Model Architecture]

B. Model Architecture Diagram

i. *Dataset Description:* The dataset employed for the detection of pneumonia is made up of chest X-ray images, mainly collected from publicly available datasets. The datasets include X-rays from anterior-posterior (AP) and posterior-anterior (PA) views, and the X-ray images are labelled as NORMAL (figure 1) or PNEUMONIA (figure 2). The dataset is usually split into training (80%) and validation (20%) to train and evaluate model performance.



[Figure 4:]

ii. *Preprocessing Techniques:* To improve the model performance, preprocessing was necessary. The following methods

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were used:

- **Image Rescaling:** All images were resized to a standard 150x150 pixel output.
- **Normalization:** Pixel values were normalized using a range of [0,1], to stabilize training.
- **Data Augmentation:** To prevent overfitting, the following augmentations were used.

iii. *Optimization Techniques:* Optimization techniques can improve model accuracy and training speed. The following methods were taken:

- **Loss Function:** Since this is a binary classification, the Binary Cross-Entropy loss has been employed.
- **Dropout Regularization (0.5):** To prevent overfitting, dropout will deactivate 50% of the neurons randomly.
- **Early Stopping:** Train until the validation loss is no longer decreasing for 5 epochs in a row.

C. Problem Statement Problems from Literature

Even though deep learning technology has improved pneumonia diagnostic systems, there are still issues, including:

i. *High False Positive Rates:* Some models are unable to differentiate normal lungs from pneumonia, which is a problem because of feature overlap.
ii. *Data Imbalance:* In public datasets, there are more instances of pneumonia than typical instances, resulting in biased models.
iii. *Domain Shift:* When X-rays are taken in different situations (e.g., from other hospitals or different X-ray machines), this can limit the generalizability of models.
iv. *Limited Interpretability:* CNNs are "black boxes," which makes their decision-making processes difficult to interpret.

II. LITERATURE SURVEY

This research focuses on diagnosing pneumonia from chest X-ray images using deep learning methods to improve accuracy and speed. We use publicly available datasets and explore pre-trained models, custom architectures, and ensemble models to improve pneumonia detection. Some limitations of the research included a lack of detail in the bespoke architectures, skewed data due to an imbalanced dataset, and a limited focus on deep learning in context. Additionally, the findings are questioned for reliability due to small-scale datasets. This highlights the importance of using balanced datasets, describing models in greater detail, and including a broader educational context to improve the reliability and reproducibility of deep learning for pneumonia detection [1].

The issue addressed is the inability to precisely detect pneumonia on chest X-ray (CXR) images, due to image quality and anatomical variations. Traditional methods rely on radiologists' subjective interpretations, leading to variability in diagnoses. This paper investigates the use of a deep learning model designed explicitly for pneumonia detection, applying advanced techniques to improve accuracy and efficiency [2].

The research addresses the detection of pneumonia from chest X-rays in the context of treating pneumonia, particularly in settings with limited resources. It uses a deep learning model rooted in the VGG-16 architecture for classification and prediction. Despite being very accurate, it depends on the quality and breadth of the dataset, which may affect its generalizability. Additionally, the model's complexity may impose heavy computational requirements, limiting its applicability in low-resource contexts. Terrific datasets and models optimized for real-world applications are needed [3].

Solves the problem of effective pneumonia detection in chest X-rays using a deep convolutional neural network that integrates EfficientNetB0 and DenseNet121, backed by attention mechanisms. The network takes 224 × 224 × 3 preprocessed input images. It has the caveat of overexposure to attention mechanisms, at the risk of 'attention redundancy,' when attention becomes too narrowly focused on localised features at the expense of including larger contextual information, which is essential for effective detection [4].

Detecting and classifying pneumonia and COVID-19 on chest X-rays is challenging because the signs of congestion are similar. The paradigm uses soft computing and deep learning, specifically an LSTM-based RNN, for classification. Disadvantages include high computational complexity, leading to longer training times and reduced robustness on larger datasets. Detection accuracy may be affected when image quality varies and noise is present [5].

This research is a response to the occurrence of child abuse among children under 5 years of age in Samarinda, Indonesia. An analytic survey was used, employing a case-control design with 21 pneumonia cases and 21 controls. Limitations include a small sample size, limited generalizability, and self-reported data on a history of disease and exposure to smoke, which could introduce confounding biases. Confounding factors, such as socioeconomic status and access to healthcare, were also omitted from the analysis, thereby reducing the comprehensiveness of the research on risk factors [6].

The issue this research addresses is the difficulty of detecting pneumonia on chest X-rays, which has traditionally relied on specialised pulmonologists and is time-consuming and specialist-driven. The process uses an automated pneumonia detection system based on deep learning, specifically a fine-tuned MobileNetV2 model. The model uses a hybrid loss function that combines focal and cross-entropy losses to address class imbalance in the dataset effectively. The work is not perfect. A potential disadvantage is that although the approach achieves high accuracy and AUC values, it may still be sensitive to the quality and diversity of the training dataset, which comprises 5,863 images and a high-class imbalance (4,280 pneumonia images and 1,583 normal images). Furthermore, random oversampling of the minority class can lead to overfitting, as the model learns to recognise unique instances rather than typical patterns. Further, the study does not account for variability in X-ray imaging technology or patient populations, which can affect the model's generalizability in real-world settings [7].

The concern discussed in this study is the classification of bilingual imaging reports

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of pneumonia, which is problematic because clinical reports were written in both Korean and English. The approach adopted a new classification algorithm that incorporated substring and Kor2Eng embeddings into an attention-based Bi-LSTM neural network (LSTM-Attention) to process and classify bilingual reports effectively. Nevertheless, the study has limitations, such as reliance on reports from a single tertiary centre, which in all likelihood could have biased the model's accuracy for practical application in other reporting contexts. This suggests re-validation across different datasets, in an exploratory manner beyond the limitations of this study, to test their robustness and generalizability. Secondly, not being able to compare it with other high-performing models directly limits the modelling examination of its impact. These highlight the need for more intensive validation and research to support systematic comparisons and improve the models' generalizability [8].

The problem addressed in this study is multidrug-resistant (MDR) Klebsiella pneumoniae, which is challenging to treat due to its polymicrobial nature and a capsule that impairs the efficacy of phage therapy. The method is phage isolation and characterisation of serotypes with reference strains, and focuses on receptor-binding proteins (RBPs) to assess specificity and therapeutic effectiveness. The limitations include limited availability of clinical isolates of K. pneumoniae, which may not capture its strain diversity, and reliance on quantitative spot tests to assess phage activity, which can introduce variability in test outcomes. Clinical isolates also exhibit stronger to moderate phage resistance mechanisms than reference strains, ultimately limiting the results of broad-range phage cocktails. These challenges illustrate the need for more representative studies and improved testing mechanisms [9].

This research addresses the challenge of accurately diagnosing pneumonia from chest x-ray images while operating in the context of limited medical training datasets. The method uses an attention-aware CNN with channel and spatial attention modules to improve feature extraction and classification accuracy. Limitations include reliance on publicly available datasets that may not reflect real cases, and the potential for overfitting despite data augmentation. Additionally, increased complexity can result in slower training and higher computational costs, limiting deployment for wider clinical use. All these considerations underscore the need for robust datasets and optimised models for actual implementation [10].

The issue addressed in this paper is finding an effective way to classify pneumonia from chest X-ray (CXR) images, particularly when using a small dataset. Standard convolutional neural networks (CNNs) often do not perform well on small datasets, making it difficult for them to classify pneumonia accurately. This study devised a new methodology that used transfer learning utilizing pre-trained models to improve classification performance [11].

The challenge addressed by this research is the need for accurate multi-class classification of chest X-ray (CXR) images for the detection of COVID-19 and other types of pneumonia, as most current approaches rely solely on binary classification. We have proposed a transfer learning approach that leverages a pre-trained AlexNet model for doing two-way, three-way, and four-way CXR image classifications. A significant drawback of this work is its reliance on a small dataset of patients with COVID-19 pneumonia, which diminishes generalizability and increases the risk of overfitting. Even if the model is found to be accurate for this, a limited dataset can never reliably represent an entire population. Future work is planned to address this by obtaining larger datasets and examining deeper neural networks to improve performance and reliability [12].

This work addresses the inadequate multi-class classification of chest X-ray (CXR) images for COVID-19 and various types of pneumonia, as most prior work focuses on binary classification and does not explicitly address the multi-class case. The method uses a transfer learning technique with a pretrained AlexNet model trained to perform multi-class classification of CXR images into no pneumonia and pneumonia of two, three, or four types. The primary limitation is the small COVID-19 pneumonia dataset, which limits generalizability and could lead to overfitting. The model would then struggle to be deployed across various populations, and high precision would not accurately reflect the complexities of real-world scenarios. Future work should explore larger datasets and potentially deeper models to make it more robust and functional [13].

The issue being investigated is the prompt diagnosis of pneumonia, a severe respiratory infection that can be life-threatening, especially in children aged under five years. Access to standard diagnostic techniques is limited in many regions, particularly in underdeveloped and developing countries, making computer-aided systems essential for diagnostic improvement. The method employs a Convolutional Neural Network (CNN) ensemble model of varied kernel sizes (3 × 3, 5 × 5, or 7 × 7) and combines the outputs via weighted averages to yield maximized diagnostic functionality. The model ultimately produces a high recall but comparatively lower accuracy and precision. These reasons have been attributed to a small dataset and to possible overfitting. To improve applicability and performance, larger, more diverse datasets, as well as alternate X-ray viewpoints, are considered reasonable [14].

This paper addresses the concern of high child mortality rates due to pneumonia, coupled with difficulty in diagnosis and expensive diagnostic tests, especially in developing countries. In this study, we propose a computer-assisted detection system for an accurate and efficient diagnosis of pediatric pneumonia using chest X-ray images. The proposed method is a stacked ensemble learning approach using the Xception model for feature extraction, Kernel PCA for dimension reduction, and a stacking classifier comprising Nu-SVC, an XGB classifier, and Logistic Regression for prediction. Limitations include reliance on a single architecture (Xception), which may be less generalizable to the data, and overfitting due to a training dataset with limited diversity. Furthermore, computationally intensive models that require significant training time may limit their real-time clinical use [15].

This research paper deals with the problem of accurately detecting pneumonia in chest X- rays- ray images—an essential step in timely diagnosis and

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treatment within radiology evaluations—can be particularly challenging. The procedure employs the QCSA network (Quaternion Channel-Spatial Attention Network), which integrates a quaternion residual network with spatial and channel attention mechanisms applied to feature maps to achieve the best classification performance. The attention mechanism could improve accuracy; however, it will likely impose a higher computational load, limiting its use in real-time clinical applications. Secondly, training on a fixed Kaggle dataset limits the model's robustness in real-world or other datasets. These limitations also acknowledge the need for further optimization and testing with larger datasets [16].

This research focuses on the three-class classification of chest X-ray images into bacterial pneumonia, viral pneumonia, and healthy lungs —an imperative step toward accurate diagnosis and treatment. The combination of an artificial neural network (ANN) with pre-trained convolutional neural network (CNN) architectures—ResNet, Inception, and MobileNet—as the feature extractor is used to enhance classification performance. However, this research incurs significant computational costs due to large images, which may hinder its deployment in a meaningful real-world framework. In addition, experiments with regularisation techniques such as dropout and batch normalisation showed that overfitting could not be entirely avoided, potentially affecting the models' generalizability and robustness. These limitations indicate a need for improved optimization and efficacy [17].

This paper addresses the need for robust methods to diagnose pneumonia and assess severity from CXR images, particularly in the context of COVID-19, where effective computational methods would be helpful to medical personnel. The technique, Vision Transformer Regressor Infection Prediction (ViTReg-IP), uses a vision transformer architecture with a regression head to assess disease severity. One limitation is that the ability to augment data is constrained because there is no a priori-annotated data with separate left- and right-lung scores. Also, reliance on a single dataset will limit the model's generalizability across clinical settings, underscoring the need for larger, well-annotated datasets to improve performance and utility [18].

The problem addressed in this work is the difficulty of accurately diagnosing pneumonia from Chest X-ray images, due to the imbalance in the class distribution of typical and pneumonia cases in the training data. This work utilises Multilayer Perceptron (MLP) and k-Nearest Neighbours (k-NN) machine learning algorithms to classify images using textural features extracted from preprocessed images via techniques such as Histogram Equalisation and Otsu thresholding. While this work has merit, a limitation is the lack of adequate photos in both the regular and pneumonia classes, which may affect classification performance. The class imbalance issue is addressed in this work through

The use of the Synthetic Minority Over-Sampling Technique (SMOTE) to create synthetic training samples, applied only to the imbalanced data set and descriptors, biases the imbalance in the original class dataset, thereby limiting optimal classification performance [19].

The issue explored in this paper is the accurate diagnosis of pneumonia from chest X-ray (CXR) images, especially the identification of subtle pathological lung textures such as ground-glass opacification, which is difficult for traditional algorithms and some deep learning techniques. To address these issues, we develop a new method for pneumonia classification called PneuNet, a Vision Transformer (ViT)-based model with a ResNet18 feature-learning backbone that utilises multi-head attention over channel patches to enhance pneumonia classification. However, while this method is optimised for pneumonia classification, it performs worse than alternative CNN-based models (e.g., LDC-NET) for multi-category classification, due to the more limited view of lung texture in CXR compared to CT. Additionally, reliance on ResNet18 as the backbone limits the model's ability to capture deeper latent patterns in the features/residuals, and the model's black-box nature limits its interpretability, which is problematic for clinical utility [20].

III. METHODOLOGY

Proposed PulmoScan: A Deep Learning Framework for Pneumonia Detection using X-Ray Images. The algorithm uses a custom Convolutional Neural Network (CNN) to extract features from images and automatically classify them. The model is trained with data augmentation to improve generalisation and reduce overfitting. The algorithm contains two main modules: Data Preprocessing and Model Training and Evaluation. The preprocessing module contains tasks for image resizing, normalization, and augmentation, while the training module contains tasks for building, training, and evaluating the CNN model. The model is optimised with the Adam optimiser and evaluated using metrics such as accuracy, precision, recall, and F1-score. The algorithm is divided into two main modules:

- Data Preprocessing Module
- Model Training & Evaluation Module

A. Module 1: Data Preprocessing

This module focuses on preparing the dataset for training. The steps include resizing images, normalising pixel values, and applying data augmentation techniques to improve the model's generalisation to unseen data.

i. Image Resizing and Normalization:

- All images are resized to 150x150 pixels to ensure uniformity.
- Pixel values are normalized to the range [0, 1] by dividing by 255 for faster convergence during training.

ii. Data Augmentation:

Various augmentation techniques are applied to increase dataset diversity and prevent overfitting:

- **Rotation:** Up to 20 degrees.
- **Width and Height Shifting:** Up to 20% of the image size.
- **Shearing and Zooming:** Up to 20%.
- Horizontal Flipping.
- **Missing Pixels Handling:** Using the 'nearest' method.

iii. Train-Validation Split:

The dataset is split into training (80%) and validation (20%) subsets using Image

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Data Generator. Two generators are defined:

- **Train_Generator:** For training data, shuffling is enabled.
- **Val_Generator:** For validation data, shuffling is disabled.

B. Module 2: Model Training & Evaluation

This module involves designing, training, and evaluating a custom CNN model using the preprocessed data.

i. Custom Deep Learning Model:

The CNN model consists of the following layers:

- **Convolutional Layers:** Three convolutional layers with 16, 32, and 64 filters, respectively, using 3x3 kernels with ReLU activation for feature extraction.
- **Max Pooling Layers:** Applied after each convolutional layer to reduce spatial dimensions while retaining essential features.
- **Flatten Layer:** Converts the 2D feature maps into a 1D vector.
- **Dense Layer:** A fully connected layer with 128 units using ReLU activation for complex pattern learning.
- **Dropout Layer:** A dropout rate of 0.5 is used to prevent overfitting.
- **Output Layer:** A single unit with a sigmoid activation function for binary classification (Normal vs. Pneumonia).

ii. Mathematical Description:

Convolution Operation:

$$y[i,j] = \sum_{m,n} x[i+m, j+n] \cdot w[m,n] \qquad (1)$$

Max Pooling:

$$y[i,j] = \max_{m,n \in P} x[i+m, j+n] \qquad (2)$$

Sigmoid Activation:

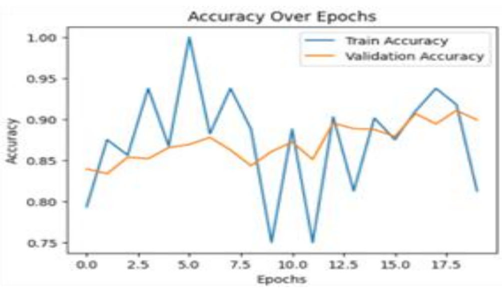
$$\sigma(z) = \frac{1}{1+e^{-z}} \qquad (3)$$

iii. Model Evaluation:

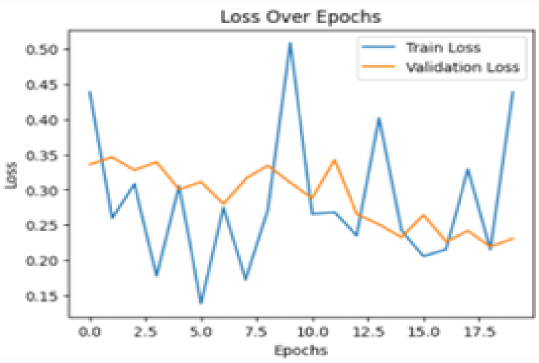
The model is evaluated using the Confusion Matrix and Classification Report.

- **Metrics:** Accuracy, Precision, Recall, and F1-Score.
- Performance metrics are visualised through line plots and bar graphs.

IV. RESULTS



[Fig.5: Accuracy Over Epochs]



[Fig.6: Loss Over Epochs]

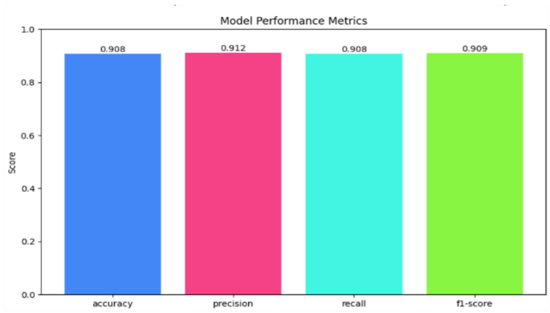
A. Optimization Techniques:

- Optimizer: Adam Optimizer combines AdaGrad and RMSProp benefits with adaptive learning rates.
- Loss Function: Binary Cross-Entropy Loss, suitable for binary classification tasks.

B. Overfitting & Underfitting:

i. Overfitting Mitigation:

- Adding a dropout layer with a rate of 0.5.
- Applying data augmentation to enhance dataset diversity.
- Limiting training epochs to 20. Underfitting:
- No significant underfitting was observed, as the model achieved high accuracy on both training and validation datasets.



[Fig.7: Model Performance Metrics]

V. RESULT ANALYSIS

A. Custom Model (Simple CNN Model)

Precision, recall, and F1-score are higher for detecting pneumonia (0.93, 0.94, 0.93) than typical cases (0.81, 0.81, 0.81). The training accuracy fluctuates more than the validation accuracy, indicating potential overfitting. The loss curves are irregular but generally decreasing, suggesting the model is learning despite instability. Improving training stability and regularization techniques may enhance performance and re- duce overfitting.

Table I Custom Model Performance

Class	Precision	Recall	F1-Score	Support
Normal	0.81	0.81	0.81	268
Pneumonia	0.93	0.94	0.93	775
Accuracy: 0.90				
Macro Avg: 0.87, 0.87, 0.87 Weighted Avg: 0.90, 0.90, 0.90				

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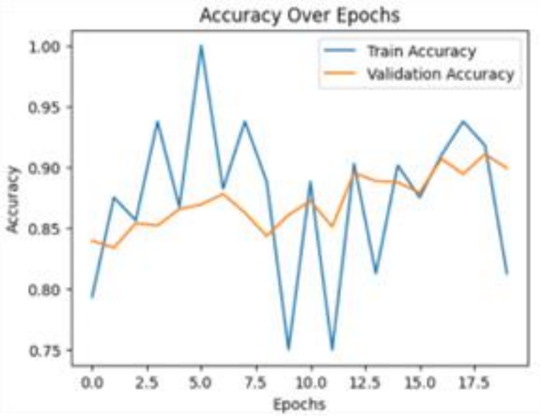
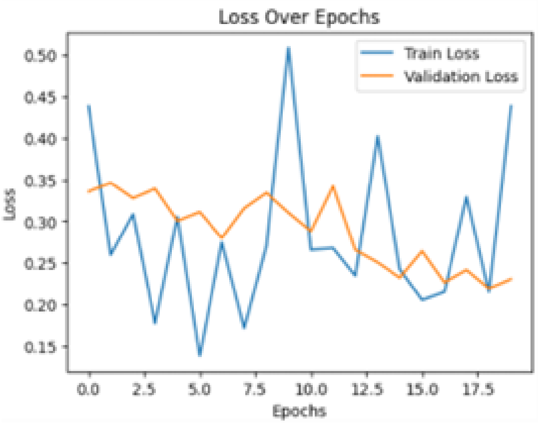


[Fig.8: Accuracy Over Epochs]



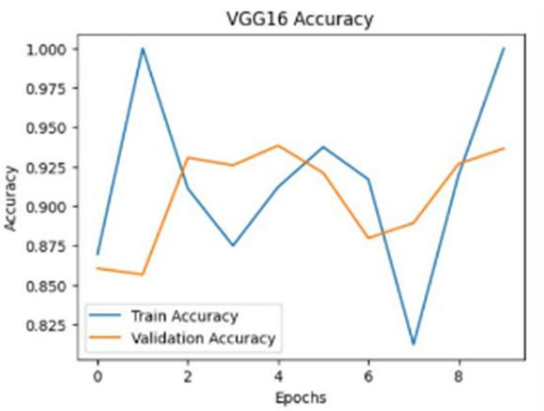
[Fig.9: Loss Over Epochs]

B. Vgg16 Model

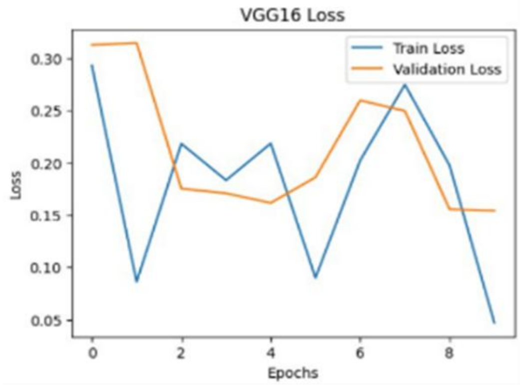
The model is VGG16, achieving 94% accuracy in pneumonia detection. Pneumonia detection metrics are high: precision (0.97), recall (0.95), and F1-score (0.96). Training accuracy shows instability, suggesting overfitting, while validation accuracy is smoother but lower. The training loss is decreasing, but the validation loss shows fluctuations, indicating learning issues or data imbalance. Improving generalisation via data augmentation, dropout, or fine-tuning the learning rate may help stabilise validation performance.

Table II: VGG16 Model Performance

Class	Precision	Recall	F1-Score	Support
Normal	0.87	0.90	0.89	268
Pneumonia	0.97	0.95	0.96	775
Accuracy: 0.94				
Macro Avg: 0.92, 0.93, 0.92 Weighted Avg: 0.94, 0.94, 0.94				



[Fig.10: VGG16 Accuracy]



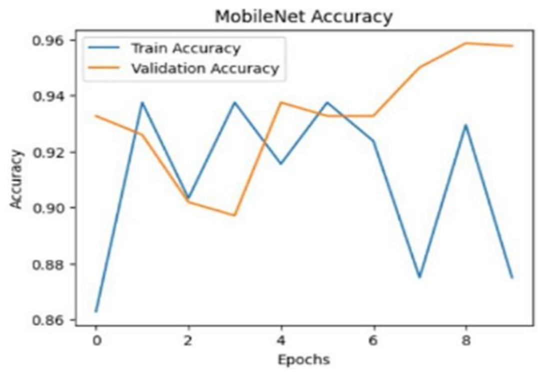
[Fig.11: VGG16 Loss]

C. Mobilenet

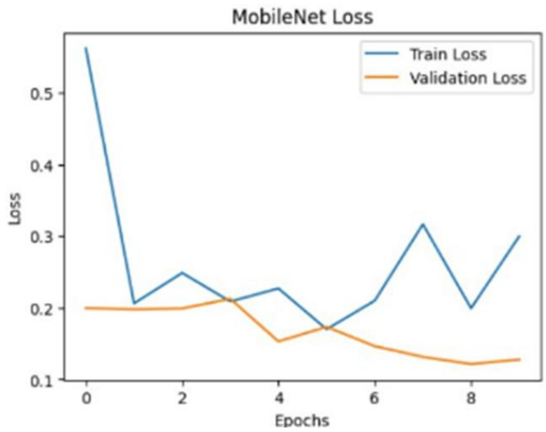
The model is MobileNet, achieving 96% accuracy in pneumonia detection. Both classes show high metrics: precision (0.93-0.97), recall (0.92-0.98), and F1-score (0.96-0.97). Training accuracy is unstable, but validation accuracy shows a steady upward trend, indicating good generalization. To improve stability, tried fine-tuning learning rates and applying dropout.

Table III MobileNet Model Performance

Class	Precision	Recall	F1-Score	Support
Normal	0.93	0.92	0.93	268
Pneumonia	0.97	0.98	0.97	775
Accuracy: 0.96				
Macro Avg: 0.95, 0.95, 0.95 Weighted Avg: 0.96, 0.96, 0.96				



[Fig.12: MobileNet Accuracy]



[Fig.14: MobileNet Loss]

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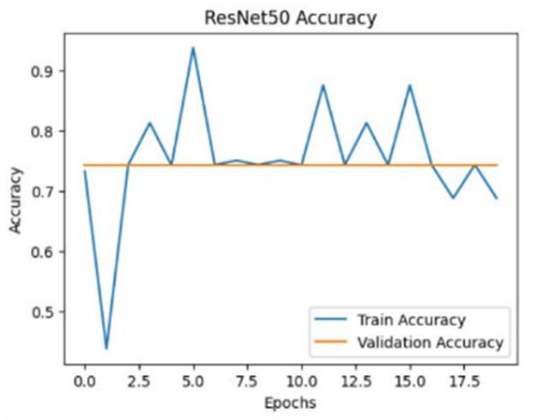
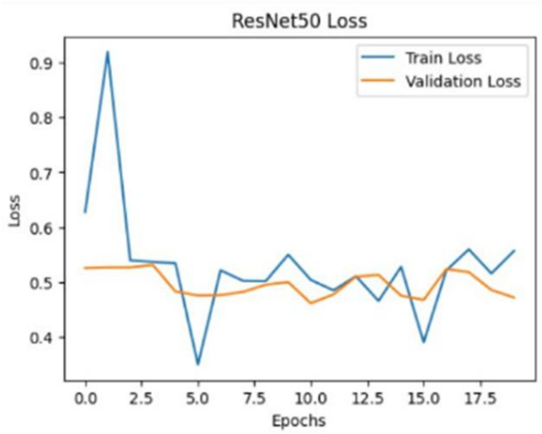


[Fig.15: ResNet50 Accuracy]

D. Resnet



[Fig.13: ResNet50 Loss]

E. Inceptionnet

The model is InceptionV3, achieving high recall for Normal (0.97) but lower precision (0.68), yielding a moderate F1 score (0.80). Pneumonia detection has excellent precision (0.99) but lower recall (0.84). Accuracy is decent (0.87) but not ideal. Training accuracy is unstable, and validation accuracy is relatively steady. The training loss decreases initially, then rises, indicating overfitting. Validation loss remains flat, further confirming this issue.

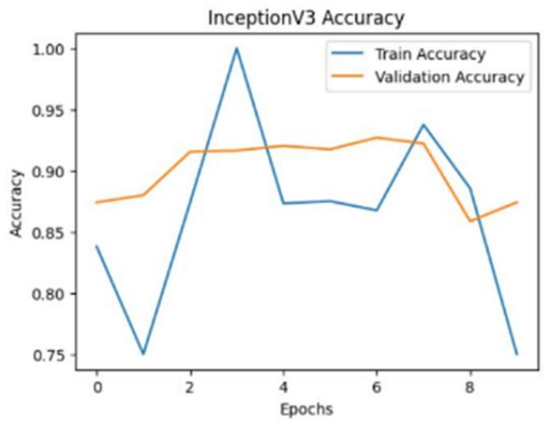
F. Improvements:

i. Reduce model complexity or use regularisation.
ii. Increase training data through augmentation.
iii. Apply techniques like dropout or early stopping.

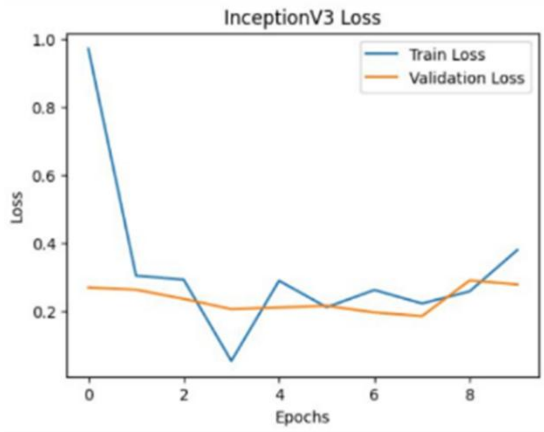
The model is ResNet50, struggling with generalization. Training accuracy fluctuates widely, while validation accuracy remains flat (0.7), indicating overfitting. Training loss decreases, but validation loss remains nearly constant, confirming poor learning. To improve performance, consider reducing model complexity, using data augmentation, tuning hyperparameters, or applying techniques such as dropout and batch normalisation.

Table IV Inceptionv3 Model Performance

Class	Precision	Recall	F1-Score	Support
Normal	0.68	0.97	0.8	268
Pneumonia	0.99	0.84	0.91	775
Accuracy: 0.87				
Macro Avg: 0.83, 0.91, 0.85 Weighted Avg: 0.91, 0.87, 0.88				



[Fig. 16: InceptionV3 Accuracy]



[Fig. 17: InceptionV3 Loss]

VI. CONCLUSION

We propose this method to improve pneumonia detection accuracy and reduce classification problems. To counter these problems, we introduce 2 crucial modules: Data Preprocessing and Model Training and Evaluation. The Preprocessing module produces uniform images by resizing, normalising, and augmenting them. The Training and Evaluation module consists of the model architecture, including convolutional layers, dropout regularisation, and the Adam optimiser. In summary, the modules reinforce model generalization and aim to reduce problems such as overfitting. The proposed algorithm outperforms existing architectures in terms of accuracy, precision, recall, and F1-score, demonstrating strong real-time performance for pneumonia detection.

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After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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