Assignment on

PNEUMONIA DETECTION USING DEEP LEARNING

Submitted in partial fulfilment of the requirements for the course

CSE2009 : SOFT COMPUTING

By

TUMARADA KOOJITHA - 22BCE7087

KONDURU RACHITHA - 22BCE9670

A DIVYA HARSHITHA - 22BCE9960

Guided by

Dr. ELANGOVAN RAJALAKSHMI

SCOPE, VIT-AP UNIVERSITY

Beside AP Secretariat, Amaravati, Andhra Pradesh

Table of Contents

Chapter1:Introduction.. 4
1.1 Introduction..4
1.2 Motivation & Relevance 4
1.2.1 Motivation...4
1.2.2 Relevance..4
1.3 Objective 5
1.3.1 Main Objective...5
1.3.2 Specific Objective 5
1.4 Problem Statement
Chapter2:Literature review 6
2.1 A hybrid deep learning approach towards building an intelligent system for pneumonia detection in chest X-ray images..6
2.2 A Deep Learning based model for the Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks..6
2.3 Detection of Pneumonia from Chest X-ray Images Utilising MobileNet Model......6
2.4 Pneumonia Recognition by Deep Learning: A Comparative Investigation 7
2.5 Pneumonia detection in chest X-ray images using an ensemble of deep learning models 7
2.6 Improving Pneumonia Detection in Chest X-rays using Transfer Learning Approach (AlexNet) and Adversarial Training... 8
2.7 A Systematic Literature Review on Deep Learning Approaches for Pneumonia Detection Using Chest X-ray Images.. 8
2.8 Pneumonia Detection using Deep Learning.. 9
2.9 A hybrid deep convolutional neural network model for improved diagnosis of Pneumonia.. 9
2.10 Comparison Table 10
Chapter 3:Methods **17**
3.1 Existing Model 1: VGG16 17
3.1.1 Description 17
3.1.2 Architecture Diagram... 19
3.2 Existing Model 2:ResNet 50 19
3.2.1 Description 19
3.2.2 Architecture Diagram... 23
3.3 Proposed Model : PneumoniaNet 24
3.3.1 Description 24
3.3.2 Architecture Diagram... 26
Chapter 4:Results and Analysis.. **27**

4.1 Dataset Description 27
4.2 ResNet 50 Results 27
4.3 VGG16 Results 29
4.4 PneumoniaNet Results 30
Chapter 5: Conclusion and Future work **32**
5.1 Conclusion 32
5.2 Future Scope 32
References **34**

Chapter 1: Introduction

1.1 Introduction

Pneumonia is a severe respiratory infection that affects millions of people worldwide, primarily young children and the elderly. Traditional techniques of diagnosing pneumonia require radiologists to manually review chest X-ray pictures, which can be time-consuming and error-prone. The incorporation of deep learning, particularly Convolutional Neural Networks (CNNs), offers the potential to automate and improve the accuracy of pneumonia detection, making it faster and more dependable. Recent advances in deep learning have demonstrated tremendous promise in the field of medical imaging, resulting in better diagnostic tools

1.2 Motivation & Relevance

1.2.1 Motivation:

Our main motivation behind this project is to create an effective and accurate pneumonia detection system utilising deep learning techniques that will help healthcare professionals diagnose pneumonia more effectively. By automating the detection process, we hope to lessen the stress on radiologists while improving patient outcomes through speedier diagnosis.

1.2.2 Relevance:

Industry Impact: This research has the potential to change pneumonia detection by developing an automated, dependable tool that can be integrated into healthcare systems, resulting in faster and more accurate diagnoses.

Scientific Contribution: The project contributes to the field of medical AI by investigating the use of CNNs for disease identification, notably in the context of pneumonia, thereby expanding the body of knowledge in medical imaging and deep learning.

Practical Benefits: The resulting system may provide practical benefits such as faster diagnosis, less human error, and improved access to diagnostic tools in underserved areas, hence improving patient care

1.3 Objective:

1.3.1 Main Objective:

To create and implement an accurate and reliable predictive model for pneumonia detection using deep learning techniques.

1.3.2 Specific Objectives:

Data Collection and Preparation: Utilizing publicly accessible datasets from sites like Kaggle, compile and preprocess a sizable collection of chest X-ray pictures with the pneumonia condition annotated.

Model Development: Create and apply deep learning models for identifying chest X-rays, concentrating on CNN architectures like VGG16, ResNet50, and MobileNetV2.

Model Evaluation: Analyze these models' performance using a variety of measures (such as accuracy, precision, and recall) and compare the outcomes to determine which method performs the best.

Model Development: Provide a mobile or online application that is easy to use so that medical professionals can apply the model in practical settings and help detect pneumonia early

1.4 Problem Statement

Pneumonia continues to be a major global cause of death, especially in areas with poor access to medical treatment. Chest X-rays were a labor-intensive, time-consuming, and human error-prone way of diagnosing pneumonia in the past. To help with prompt and efficient illness care, an automated system that can reliably identify pneumonia from chest X-ray pictures is desperately needed. Our project aims to address this problem by developing a deep learning-based predictive model that can analyze chest X-rays and identify pneumonia with high accuracy. The model will be integrated into a user-friendly application that can be used by healthcare providers to facilitate the early and accurate detection of pneumonia, especially in resource-constrained settings

Chapter 2:Literature review

MAIN POINTS IN EACH PAPER:

2.1 A hybrid deep learning approach towards building an intelligent system for pneumonia detection in chest X-ray images.(Masad, I. S., Alqudah, A., Alqudah, A. M., & Almashaqbeh, S. (2021))

Pneumonia is a leading cause of death in children, accounting for over 800,000 deaths annually, and affects adults significantly as well. Traditional pneumonia detection methods using chest X-rays can be slow and subjective, prompting the need for automated solutions. The paper proposes a hybrid deep learning system combining a Convolutional Neural Network (CNN) with classifiers like SVM, KNN, and Random Forest to improve detection accuracy. A key innovation in the study is the use of small-sized chest X-ray images (64×64 pixels) to reduce computational complexity while maintaining performance. The hybrid system demonstrates superior performance compared to traditional CNN-based models, such as CheXNet, in terms of accuracy and efficiency.
This approach shows promise for enhancing medical diagnostics, with potential for future research to further optimize speed and sensitivity.

2.2 A Deep Learning based model for the Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks(Sharma, S., & Guleria, K. (2023))

The paper presents a deep learning model using VGG-16 architecture for pneumonia detection from chest X-ray images. Pneumonia, a critical respiratory disease, requires rapid and accurate diagnosis, especially in developing countries with limited healthcare infrastructure. The proposed model focuses on overcoming the challenges of subjective variability in manual X-ray examination by automating the detection process. The study demonstrates that the VGG-16 neural network outperforms traditional machine learning models like SVM, KNN, and Random Forest. This model shows promise in improving pneumonia diagnosis accuracy, offering a reliable tool for healthcare professionals.

2.3 Detection of Pneumonia from Chest X-ray Images Utilizing MobileNet Model.(Reshan, M. S. A., Gill, K. S., Anand, V., Gupta, S., Alshahrani, H., Sulaiman, A., & Shaikh, A. (2023, May))

The paper focuses on the development of a deep learning-based approach using the MobileNet model to detect pneumonia from chest X-ray images.
Pneumonia diagnosis is challenging due to its visual similarity to other respiratory diseases like tuberculosis. Eight pre-trained models, including ResNet, DenseNet, and EfficientNet, were compared for accuracy. MobileNet achieved the best performance with a high accuracy rate. The study highlights the importance of robust algorithms to improve pneumonia detection in varying imaging conditions.

2.4 Pneumonia Recognition by Deep Learning: A Comparative Investigation(Yang, Y., & Mei, G. (2022))

Pneumonia is a significant infectious disease, and traditional manual diagnosis methods are subjective and often inefficient. This paper compares five deep learning models—LeNet5, AlexNet, MobileNet, ResNet18, and Vision Transformer—for pneumonia recognition using chest X-ray images. Each model's performance was evaluated to identify the most effective one for different dataset sizes and conditions. LeNet5 and AlexNet were found to perform better on small datasets, while MobileNet and ResNet18 excelled with larger datasets. Data augmentation did not significantly improve accuracy for small datasets, but GPU loading enhanced computational efficiency for all models.The findings aim to aid in the practical selection of deep learning models for pneumonia detection, improving diagnostic efficiency and accuracy.

2.5 Pneumonia detection in chest X-ray images using an ensemble of deep learning models(Kundu, R., Das, R., Geem, Z. W., Han, G. T., & Sarkar, R. (2021))

The paper proposes a computer-aided diagnosis system for automatic pneumonia detection using an ensemble of deep learning models. This ensemble consists of three CNN models—GoogLeNet, ResNet-18, and DenseNet-121—leveraging transfer learning for improved accuracy. A novel weighted average ensemble technique is used, assigning weights based on four evaluation metrics (precision, recall, F1-score, and AUC) rather than just accuracy. The model was tested on two public pneumonia X-ray datasets, demonstrating its superior performance compared to state-of-the-art methods. Statistical analysis using McNemar's and ANOVA tests confirmed the robustness of the proposed model, which can be applied to various computer vision tasks. The study highlights the importance of using an ensemble approach to capture complementary information from different CNN models, leading to more accurate pneumonia detection. Future work could focus on enhancing image quality through techniques like contrast enhancement or lung segmentation to further improve classification accuracy.

2.6 Improving Pneumonia Detection in Chest X-rays using Transfer Learning Approach (AlexNet) and Adversarial Training(Athar, A., Asif, R. N., Saleem, M., Munir, S., Al Nasar, M. R., & Momani, A. M. (2023, March))

The study employs AlexNet, a deep learning model, to enhance pneumonia detection using chest X-rays.Transfer learning is used to fine-tune the model, improving its feature extraction capabilities. Adversarial training introduces synthetic chest X-rays to boost model robustness and reduce overfitting. This approach improves the model's ability to generalize to new, unseen X-rays. Results show improved accuracy over prior methods.The model demonstrates potential for significant clinical applications in pneumonia diagnosis.The adversarial training technique reduces the risk of overfitting by exposing the model to both real and synthetic images, helping it handle diverse data more effectively. The paper highlights that this approach could enhance the accuracy of pneumonia diagnosis, especially in environments with limited labeled data, providing a practical tool for improving patient outcomes.

2.7 A Systematic Literature Review on Deep Learning Approaches for Pneumonia Detection Using Chest X-ray Images.(Sharma, S., & Guleria, K. (2024))

It emphasizes the growing demand for accurate, fast diagnosis in healthcare due to the increasing pneumonia cases worldwide. A variety of deep learning techniques, especially convolutional neural networks (CNNs), are discussed for their effectiveness in image-based disease detection.The review explores how advancements in medical imaging and AI can lead to earlier, more reliable diagnosis.It underscores the importance of improving model accuracy while reducing false positives and negatives.Transfer learning and pre-trained models are identified as key enablers for optimizing pneumonia detection algorithms.The paper discusses challenges like data variability, quality, and ethical considerations in AI-driven healthcare solutions.

2.8 Pneumonia Detection using Deep Learning(Mishra, S., Hazra, A., & Prakash, U. M. (2022, April))

The paper focuses on the application of deep learning techniques to detect pneumonia from chest X-ray images, addressing the growing demand for automated diagnostic tools.It reviews the advancements in deep learning models, particularly convolutional neural networks (CNNs), and their effectiveness in pneumonia detection.The authors discuss the challenges posed by variations in X-ray image quality, such as noise and differences in exposure levels, which can impact detection accuracy.The paper highlights the advantages of deep learning over traditional image processing methods, emphasizing its ability to automatically extract relevant features from medical images. Transfer learning is discussed as a useful technique for overcoming the challenge of limited labeled medical datasets in pneumonia detection.The authors emphasize the need for accurate, interpretable models that healthcare professionals can trust for decision-making in critical medical conditions. Image pre-processing techniques are noted as important for enhancing the clarity of X-ray images, thereby improving the model's ability to detect pneumonia.

2.9 A hybrid deep convolutional neural network model for improved diagnosis of pneumonia(Mann, P. S., Panchal, S. D., Singh, S., Saggu, G. S., & Gupta, K. (2024))

The paper introduces a hybrid deep convolutional neural network (HDCNN) model to enhance pneumonia diagnosis from chest X-ray images. Pneumonia is a major cause of death, especially in children, and early detection is crucial for treatment. The authors emphasize the need for AI-based techniques to support medical professionals in timely and accurate diagnosis. By combining several pre-trained deep learning models, the proposed HDCNN model leverages advanced image preprocessing and ensemble learning to improve predictive accuracy. Grad-CAM visualization is integrated to provide visual explanations, highlighting infected regions in the X-rays, making the model more interpretable for clinical use. The paper concludes that this hybrid approach can outperform existing methods and suggests future improvements in hyperparameter tuning and medical diagnosis applications.

2.10 COMPARISON TABLE:

Sl. No	Title of the paper	Methodology	Datasets used	Performance metrics	Advantages	Disadvantages
1	A hybrid deep learning approach towards building an intelligent system for pneumonia detection in chest X-ray images.	The study proposed a hybrid deep learning system for pneumonia detection using chest X-ray images. The primary model was a convolutional neural network (CNN), which was combined with three different classifiers: support vector machine (SVM), k-nearest neighbor (KNN), and random forest (RF). The CNN with the traditional Softmax classifier was also used as a baseline for comparison. Each hybrid model used the features extracted by CNN for classification, aiming to improve the detection performance.	The dataset consisted of small-sized chest X-ray images used to evaluate the performance of the hybrid model. The exact source of the dataset is not specified, but it was likely a public dataset of pneumonia chest X-rays, which is commonly used in such research studies.	Accuracy, sensitivity, specificity, and precision were evaluated. Softmax and SVM achieved 99% accuracy, while KNN and RF had 98.5% and 97.15% accuracy, respectively. KNN was the fastest classifier, while RF had the longest classification time.	The hybrid system achieved high accuracy, comparable to or better than traditional CNN with Softmax. The KNN classifier showed significant improvement in computation time, achieving up to a fourfold increase in speed compared to other classifiers.	While the KNN classifier had the best computation time, it came at the expense of reduced sensitivity, meaning it was less effective at identifying pneumonia cases. The random forest (RF) classifier underperformed compared to other classifiers in terms of accuracy, precision, and specificity.
	A Deep Learning based model for the	The paper presents a deep learning model utilizing the VGG16 architecture for	Two datasets were used: one with 5,856 CXR	The performance was evaluated using accuracy, precision, recall, and F1-score. NN with VGG16	High accuracy in pneumonia detection (up to 95.4%).	VGG16 architecture is computationally intensive, requiring significant

2	Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks	feature extraction and Neural Networks (NN) for classification. The model is trained and tested on chest X-ray (CXR) images for pneumonia detection. Preprocessing is done to normalize the data, and various classifiers (SVM, KNN, RF, NB) are compared with the proposed NN with VGG16 model for performance.	images from pediatric patients for binary classification (pneumonia/ normal), and another with 6,436 images for multi-class classification (pneumonia, normal, COVID-19), both sourced from Kaggle	achieved 92.15% accuracy for the first dataset and 95.4% for the second dataset, outperforming other models like SVM and KNN	Effective use of VGG16 for feature extraction and NN for classification. The model outperformed other classifiers like SVM and KNN	processing time. The model is dependent on high-quality labeled datasets for optimal performance
3	Detection of Pneumonia from Chest X-ray Images Utilizing MobileNet Model.	The paper utilizes a deep-learning approach with MobileNet as the primary model, alongside seven other pre-trained models (e.g., ResNet50, DenseNet121) to detect pneumonia in chest X-ray images. Data augmentation techniques like random rotation, flipping, zooming, and brightness adjustments were applied to improve training outcomes. The models were trained with different optimizers (ADAM, ADADELTA, SGD) and batch sizes to find the best-performing configuration.	First dataset: 5856 chest X-ray images (4273 pneumonia, 1583 normal). Second dataset: ChestX-ray14 with 112,120 images, balanced to 1431 pneumonia and 1431 normal images.	Accuracy, Precision, Recall, F1-score, and Area Under the Curve (AUC) were used to evaluate the models, with MobileNet achieving the best results (accuracy of 94.23% on the first dataset and 93.75% on the second).	MobileNet demonstrated high accuracy with reduced computational complexity, making it suitable for real-time applications. Data augmentation helped to enhance the model's performance and avoid overfitting.	The model's performance may be influenced by variability in the quality of chest X-ray images, and the dataset sizes, while large, may still be limited for more diverse medical conditions beyond pneumonia detection.

4	Pneumonia Recognition by Deep Learning: A Comparative Investigation	The authors compared five deep learning models—LeNet5, AlexNet, MobileNet, ResNet18, and Vision Transformer—for pneumonia recognition using chest X-ray images. The study involved data collection, cleaning, model construction, and comparative analysis of these models under various conditions, including before and after data augmentation and GPU loading.	The dataset was acquired from Guangzhou Women's and Children's Medical Center and contained 3150 X-ray images, equally split between pneumonia and normal cases.	**LeNet5**: Achieved high recognition rates, especially effective with smaller datasets. Accuracy-93.72% **AlexNet**: this model also performed well with smaller datasets. Accuracy - 95.82% **MobileNet**: Excelled with larger datasets, showcasing strong performance in terms of both accuracy and efficiency. Accuracy - 97.60% **ResNet18**: more suitable for extensive pneumonia detection tasks. Accuracy - 98.54%	Provides a detailed comparison of deep learning models for pneumonia recognition. Offers insights into the best models based on dataset size and computing efficiency.	The dataset was small, limiting the generalizability of the findings. Data augmentation did not significantly improve accuracy for smaller datasets.
5	Pneumonia detection in chest X-ray images using an ensemble of deep learning models	The authors propose an ensemble methodology combining three pre-trained deep learning models: VGG19, ResNet50, and InceptionV3 for pneumonia detection, using transfer learning and fine-tuning on a pneumonia dataset with pre-trained ImageNet weights. It employs image preprocessing and data augmentation to enhance model generalization. Predictions are aggregated through	The system was evaluated on two publicly available datasets: the Kermany dataset and the RSNA Pneumonia Detection Challenge dataset.	The system was evaluated based on accuracy, precision, recall, F1-score, and AUC. It achieved 98.81% accuracy on the Kermany dataset and 86.85% accuracy on the RSNA dataset.	The ensemble method outperformed individual CNN models, providing better generalization and more accurate results. It uses a balanced approach by considering multiple metrics beyond just accuracy, improving robustness.	The approach is computationally expensive due to the need for training three deep learning models, and it may struggle with low-quality X-ray images.

		majority voting, improving classification accuracy by leveraging the strengths of each model. This approach aims to provide a reliable automated diagnostic tool for healthcare professionals.				
6	Improving Pneumonia Detection in Chest X-rays using Transfer Learning Approach (AlexNet) and Adversarial Training.	The paper uses transfer learning with AlexNet, a deep convolutional neural network (CNN) pre-trained on ImageNet, to extract features from chest X-rays. The network is fine-tuned on a smaller pneumonia-specific dataset. Additionally, adversarial training is employed to generate synthetic X-rays, which improves model robustness and generalization by training on both real and adversarial images.	The dataset for pneumonia detection is from Kaggle, consisting of 5,222 chest X-ray images labeled as normal or pneumonia.	The reported **accuracy** was around **98.28%**, with strong performance in other metrics as well, including **precision**, **recall**, and **F1-score** in the range of **97-98%**, highlighting the efficacy of the transfer learning and adversarial training approach	Improved accuracy and robustness for pneumonia detection due to transfer learning and adversarial training. Reduces the risk of overfitting and enhances generalization to new X-rays.	Potential overfitting due to the small dataset size. Class imbalance in the dataset might limit generalizability.

7	A Systematic Literature Review on Deep Learning Approaches for Pneumonia Detection Using Chest X-ray Images	They follow a structured process, first identifying relevant studies through database searches, then filtering based on inclusion/exclusion criteria, focusing on studies using deep learning for pneumonia detection. The authors analyze various deep learning models, including CNN-based architectures like VGG, ResNet, and Inception, often used with transfer learning. They evaluate preprocessing techniques, such as resizing, normalization, and data augmentation, used to enhance model performance. The review highlights ensemble methods and performance metrics like accuracy, sensitivity, and specificity in pneumonia detection.	The datasets used include ChestX-ray14, RSNA Pneumonia Detection, and datasets from sources like Kaggle, NIH, and hospitals like Mount Sinai and Indiana University.	Accuracy: Ranges between 85% to 98%, with ensemble methods and transfer learning. Sensitivity (Recall): Typically falls between 86% to 98% Specificity: Varies from 83% to 97% Precision: Reported between 84% to 96% F1-score: Often ranges from 85% to 97%	Provides a comprehensive comparison of DL models for pneumonia detection. Highlights the strengths of ensemble models and pre-trained networks. Emphasizes the importance of early pneumonia diagnosis using CXR images.	Limited to analyzing previously published studies, without new experimental results. Focuses mainly on CNN-based models, lacking detailed exploration of alternative techniques.
8	Pneumonia Detection using Deep Learning	The paper proposes a deep learning model based on ResNet152V2 architecture, utilizing transfer learning to detect pneumonia from	The dataset used in the paper for pneumonia detection was obtained from **Mendeley**	The fine-tuned model achieved a test accuracy of **90.7%**, with a **precision** of 0.89, **recall** of 0.98, an **F1-score** of 0.93, and an **ROC-AUC** of 0.978.	The model provides fast and accurate pneumonia detection, reducing diagnostic time and aiding early	The main limitation is the **small dataset** size, which could limit the model's performance and generalization. A larger, more complex dataset could

		chest X-ray images. The model is fine-tuned by freezing initial layers pre-trained on ImageNet and further training on pneumonia-specific data. Data augmentation was applied to address the limited dataset and prevent overfitting.	**Data**, a publicly available repository. It includes labeled chest X-ray images, with both normal and pneumonic lungs, which were used to train and test the model.		treatment. It also minimizes the need for physical contact in medical diagnosis.	enhance accuracy.
9	A hybrid deep convolution al neural network model for improved diagnosis of pneumoni	The methodology involves creating a Hybrid Deep Convolutional Neural Network (HDCNN) model for pneumonia diagnosis, starting with image preprocessing techniques like resizing, histogram equalization, and the use of Student's t distribution for better feature sampling. The model uses an ensemble of five pre-trained CNNs—ResNet-50 , VGG-16, MobileNetV2, EfficientNetB4, and DenseNet-121—fin e-tuned for pneumonia detection. The predictions from these models are averaged to improve accuracy and robustness.	The dataset contains chest X-ray images of children aged 1 to 5, collected from a Children's Medical Center in China.	**Precision**: 97.47% **Recall**: 98.09% **F1-Score**: 97.77% **Accuracy**: 97.69%	**High Accuracy**: The model achieves a superior accuracy of 97.69%, outperforming other models. **Feature Extraction**: The use of multiple pre-trained CNN models improves the extraction of complex features from X-ray images. **Efficient Preprocessing**: The application of Student's t distribution helps in better image preprocessing, improving model performance. **Visualization with Grad-CAM**: This helps medical practitioners by highlighting infected regions in the X-rays,	**Computational Complexity**: The use of multiple deep models increases the computational requirements for both training and inference. **Training Time**: The model requires a significant amount of time for training, especially with the ensemble of several large pretrained models. **Model Optimization**: Fine-tuning multiple CNNs and hyperparameters could be time-consuming and resource-intensive. **Limited Dataset**: The dataset is relatively small, which could limit generalizability, though this is mitigated by data

		Grad-CAM visualization is used to highlight infected regions in X-ray images, making the model's predictions more interpretable for medical professionals.			improving interpretability. **Ensemble Learning**: Combining the strengths of various CNN models through ensemble learning provides more robust predictions.	augmentation techniques.	

Chapter 3: Models

3.1 Existing Model 1: [VGG16]

3.1.1 Description:

The VGG16-based model is a convolutional neural network (CNN) used for binary classification, particularly to detect pneumonia from chest X-ray images. VGG16, a pre-trained model on ImageNet, serves as the feature extractor, capturing important patterns in medical imaging. The model aims to leverage the transfer learning capabilities of VGG16, where only the top layers are modified to suit the pneumonia detection task, resulting in improved performance with reduced training time and computational cost.

Purpose:

The purpose of this model is to classify chest X-ray images as either pneumonia-positive or pneumonia-negative. By freezing the pre-trained VGG16 layers, the model efficiently transfers the learning from a general image dataset to the specific task of medical image classification, minimizing the need for large amounts of pneumonia-specific data.

Key Components:

Input Layer: Accepts input images with a shape of (256, 256, 3), representing resized chest X-ray images.

Pre-trained VGG16 Base Model:
Loaded with pre-trained weights from ImageNet and includes all layers up to the final pooling layer. This base model acts as a feature extractor, providing high-level feature maps for pneumonia classification.

All layers in the base model are frozen to retain pre-trained knowledge, preventing them from being updated during training.

Global Average Pooling Layer:

Reduces the dimensionality of the feature maps from the VGG16 base model while retaining important information by applying a global average pooling operation. This serves as a transition from the convolutional layers to the fully connected layers.

Dense Output Layer:

A fully connected layer with a single neuron to perform binary classification. Since pneumonia detection is a binary task, the model outputs a single value (logits) that is processed by a sigmoid activation to yield a probability.

Loss and Optimization:

Loss Function: Binary Crossentropy with logits to handle binary classification tasks efficiently.

Optimizer: Adam optimizer with a learning rate of 1e-3 is used to update the model's trainable weights.

Evaluation Metrics:

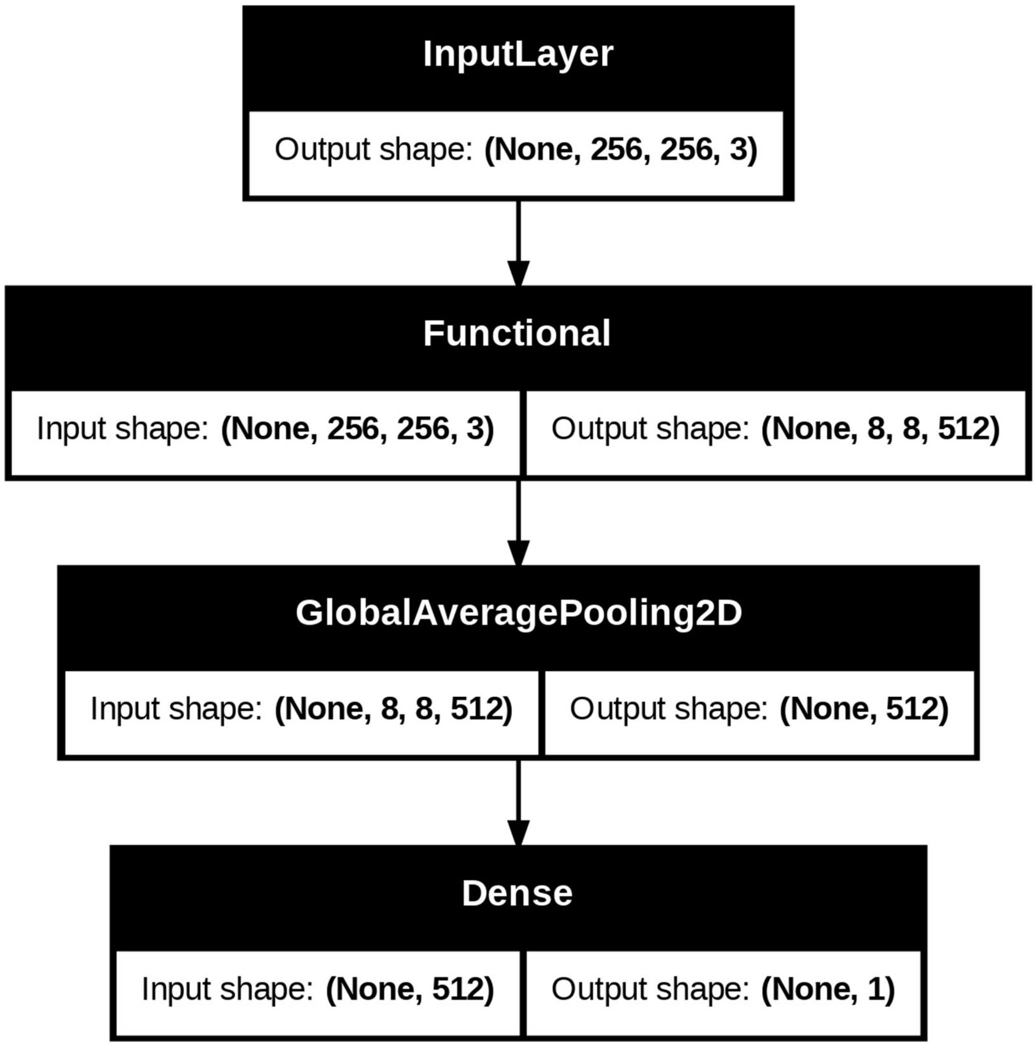
The model tracks three key metrics: accuracy, precision, and recall, ensuring a balanced evaluation of classification performance, especially for medical data where misclassifications could be critical.

Model: "functional_1"

Layer (type)	Output Shape	Param #
input_layer_2 (InputLayer)	(None, 256, 256, 3)	0
vgg16 (Functional)	(None, 8, 8, 512)	14,714,688
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dense (Dense)	(None, 1)	513

Total params: 14,716,229 (56.14 MB)
Trainable params: 513 (2.00 KB)
Non-trainable params: 14,714,688 (56.13 MB)
Optimizer params: 1,028 (4.02 KB)

3.1.2 Architecture Diagram:



3.2 Existing Model 2: [ResNet50]

3.2.1 Description:

The ResNet50-based model is a convolutional neural network (CNN) designed for binary classification tasks, specifically detecting pneumonia from chest X-ray images. The model leverages ResNet50, a deep residual network pre-trained on ImageNet, as the feature extractor. The ResNet50 base layers are fine-tuned selectively to further improve the model's performance on the medical dataset.

Custom layers are added on top of the base model to suit the task of binary pneumonia classification.

Purpose:

The model is designed to classify chest X-ray images into pneumonia-positive or pneumonia-negative categories. By fine-tuning specific layers of the ResNet50 model, it optimizes the feature extraction for the medical images in the dataset while maintaining the efficiency and robustness of pre-trained layers.

Key Components:

- **Input Layer:**
  - Accepts input images with dimensions of (256, 256, 3) for chest X-rays.
- **Pre-trained ResNet50 Base Model:**
  - Utilizes the ResNet50 architecture with pre-trained weights from ImageNet. This model is known for its deep residual connections that allow for efficient training and the avoidance of vanishing gradient problems in deep networks.
  - Layers up to a specified point (fine_tune_at = 10) are frozen to retain the pre-trained knowledge, while the last 10 layers are unfrozen and made trainable for further fine-tuning.
- **Fine-tuning Layer Strategy:**
  - Fine-tunes the last 10 layers of the ResNet50 base model to better adapt to pneumonia detection by allowing the model to learn features specific to the X-ray dataset while keeping most of the base model's layers frozen to avoid overfitting.
- **Custom Fully Connected Layers:**
  - **Global Average Pooling Layer:**
    Reduces the spatial dimensions of the feature maps while retaining the most important information from the ResNet50 base.
  - **Dense Layers:**
    Two fully connected layers with 256 and 64 neurons respectively, using ReLU activation and L2 regularization to reduce overfitting.

Batch Normalization:
Applied after each dense layer to stabilize and accelerate the training process.
Dropout:
Dropout layers with dropout rates of 0.4 and 0.2 are used to further prevent overfitting by randomly disabling neurons during training.

Output Layer:

A single neuron output layer for binary classification. The output is processed as logits (before applying a sigmoid activation to obtain a probability).

Loss and Optimization:

Loss Function:
Binary Crossentropy with logits, suited for binary classification tasks.

Optimizer:
Adam optimizer with a very low learning rate (1e-5) is used for fine-tuning to prevent large weight updates that could destroy pre-trained knowledge.

Evaluation Metrics:
Tracks accuracy, precision, and recall, which are critical for medical image classification where false positives and false negatives have significant consequences.

Model: "functional_2"

Layer (type)	Output Shape	Param #
input_layer_4 (InputLayer)	(None, 256, 256, 3)	0
resnet50 (Functional)	(None, 8, 8, 2048)	23,587,712
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 2048)	0
dense_1 (Dense)	(None, 1)	2,049

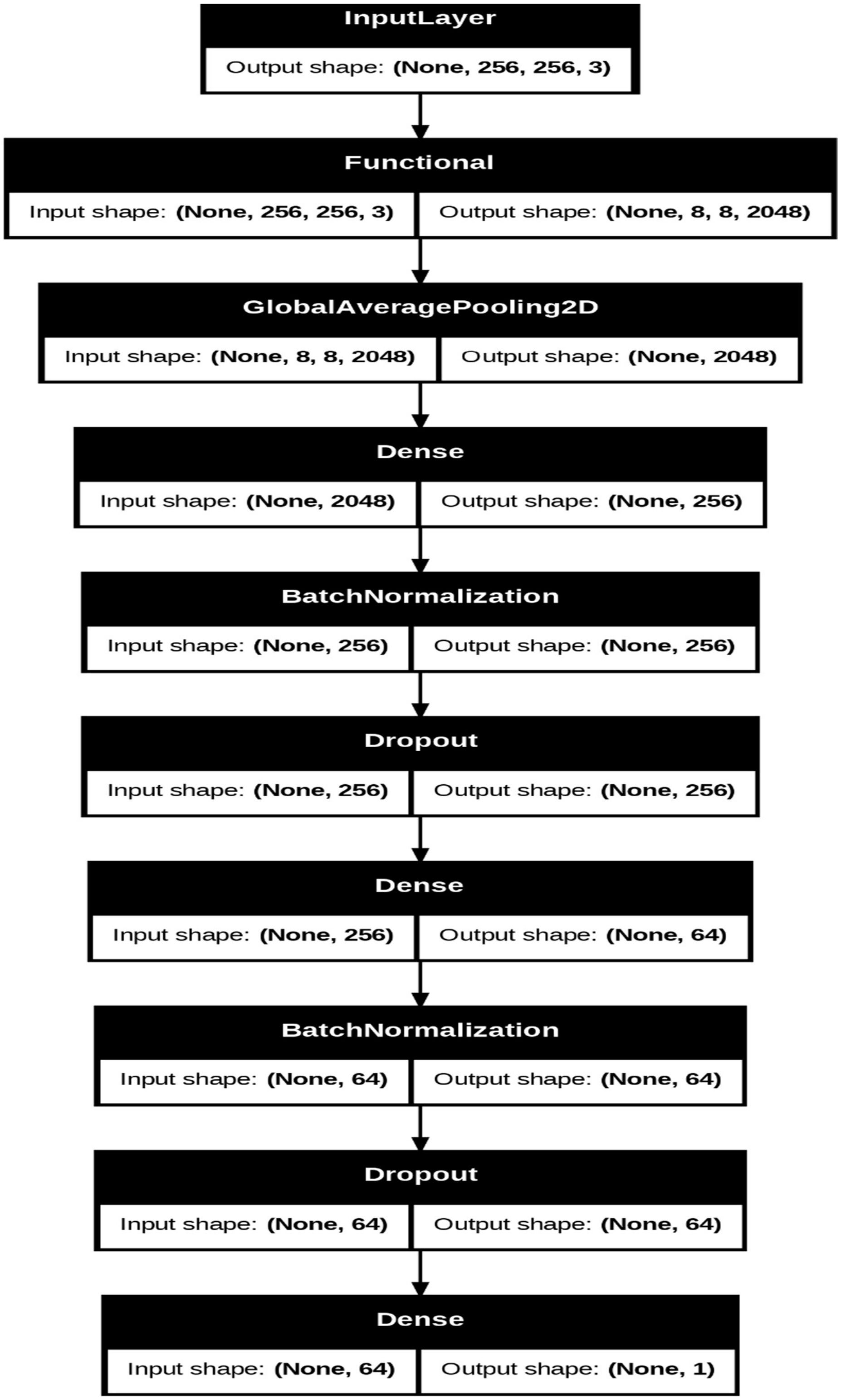
Total params: 23,593,861 (90.00 MB)
Trainable params: 2,049 (8.00 KB)
Non-trainable params: 23,587,712 (89.98 MB)
Optimizer params: 4,100 (16.02 KB)

Model: "functional_6"

Layer (type)	Output Shape	Param #
input_layer_12 (InputLayer)	(None, 256, 256, 3)	0
resnet50 (Functional)	(None, 8, 8, 2048)	23,587,712
global_average_pooling2d_5 (GlobalAveragePooling2D)	(None, 2048)	0
dense_5 (Dense)	(None, 256)	524,544
batch_normalization_282 (BatchNormalization)	(None, 256)	1,024
dropout (Dropout)	(None, 256)	0
dense_6 (Dense)	(None, 64)	16,448
batch_normalization_283 (BatchNormalization)	(None, 64)	256
dropout_1 (Dropout)	(None, 64)	0
dense_7 (Dense)	(None, 1)	65

Total params: 24,130,049 (92.05 MB)
Trainable params: 5,007,361 (19.10 MB)
Non-trainable params: 19,122,688 (72.95 MB)

3.2.2 Architecture Diagram:



3.3 Proposed Model: [PneumoniaNet]

3.3.1 Description:

PneumoniaNet is a custom convolutional neural network (CNN) developed specifically for detecting pneumonia in chest X-ray images. Its design aims to streamline the detection process by utilising a lean yet powerful architecture that effectively balances accuracy with computational efficiency, making it suitable for both high-performance servers and lower-resource environments, like mobile devices or clinics.

Purpose:

The goal of PneumoniaNet is to accurately classify chest X-rays as pneumonia-positive or pneumonia-negative, providing a quick diagnostic aid to medical professionals. PneumoniaNet improves upon existing models by reducing the dependency on extensive pre-trained networks, which can be computationally expensive, and instead focuses on achieving high performance with a custom architecture tailored to pneumonia detection.

Key Features:

Custom CNN Layers:

PneumoniaNet's structure includes multiple convolutional layers to extract detailed features from X-ray images, capturing subtle patterns associated with pneumonia.

Data Augmentation and Dropout:

Data augmentation helps improve generalisation by simulating variations in input images, while dropout layers reduce overfitting, enhancing model robustness.

Binary Classification Output:

The final output layer uses a sigmoid activation, making it ideal for binary classification (pneumonia-positive vs. pneumonia-negative).

Components and Workflow:

Input Layer: The model accepts 256x256 pixel images, optimising the input size for memory usage and efficient processing without compromising detail.

Convolutional and Pooling Layers: Four convolutional layers progressively increase in depth (from 32 to 256 filters), each followed by max-pooling layers. These layers help the model capture essential spatial hierarchies in X-ray imagery.

Flatten Layer: The flattened output from the convolutional layers prepares the data for fully connected layers by transforming it into a one-dimensional array.

Dense and Dropout Layers: A fully connected dense layer with 512 units refines the features, while a dropout layer with a 50% rate prevents overfitting, especially crucial for limited datasets.

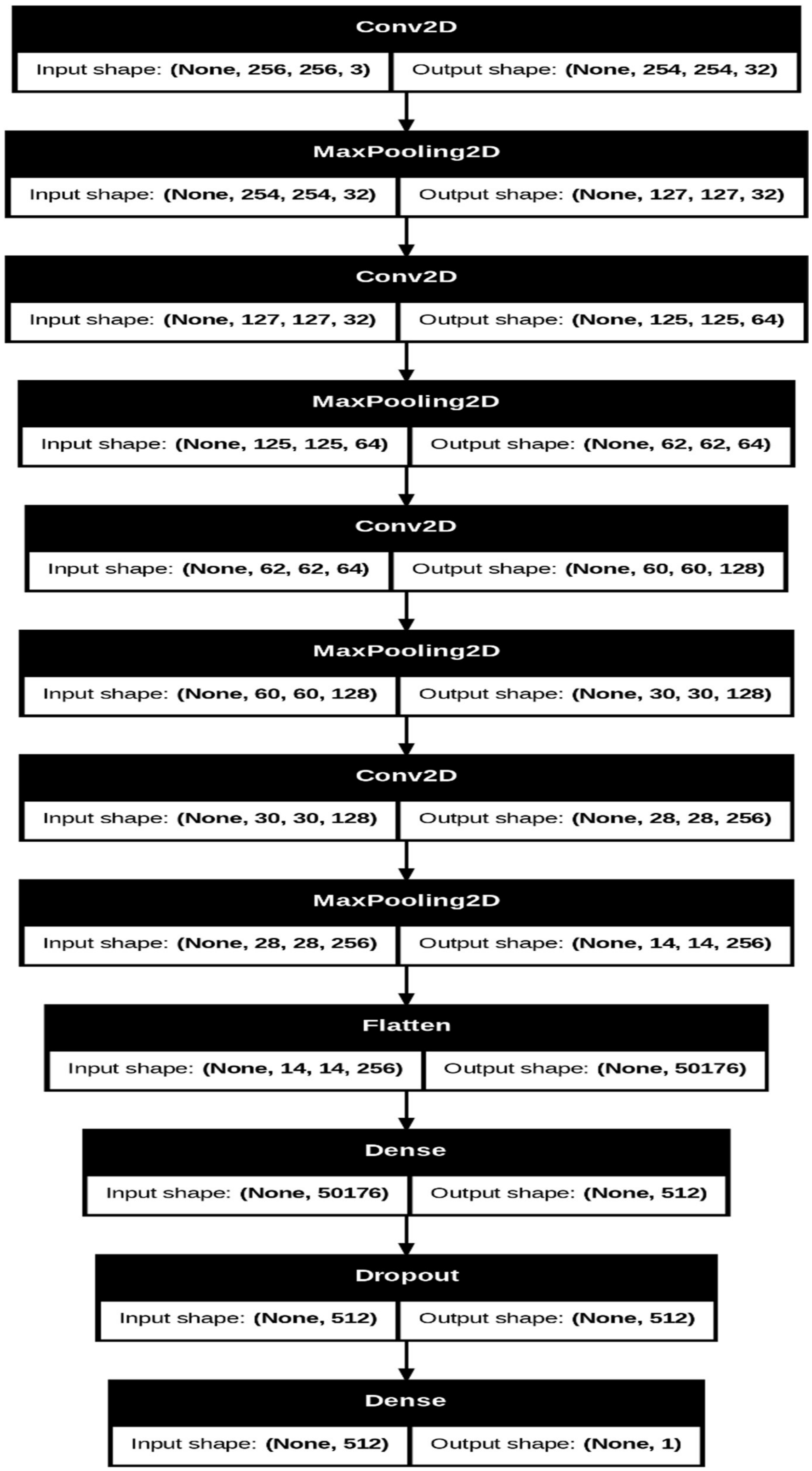
Output Layer: A single dense unit with sigmoid activation provides a binary classification output, indicating the presence or absence of pneumonia.

This workflow allows PneumoniaNet to process X-ray images from raw pixels to a final prediction, with each component contributing to the model's ability to generalise well on new data while maintaining simplicity and speed.

Layer (type)	Output Shape	Param #
conv2d_36 (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d_36 (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_37 (Conv2D)	(None, 125, 125, 64)	18,496
max_pooling2d_37 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_38 (Conv2D)	(None, 60, 60, 128)	73,856
max_pooling2d_38 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_39 (Conv2D)	(None, 28, 28, 256)	295,168
max_pooling2d_39 (MaxPooling2D)	(None, 14, 14, 256)	0
flatten_9 (Flatten)	(None, 50176)	0
dense_18 (Dense)	(None, 512)	25,690,624
dropout_9 (Dropout)	(None, 512)	0
dense_19 (Dense)	(None, 1)	513

```
Total params: 78,238,661 (298.46 MB)
Trainable params: 26,079,553 (99.49 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 52,159,108 (198.97 MB)
```

3.3.2 Architecture Diagram:



Chapter 4: Results and Analysis

4.1 Dataset Description

In this study, we utilised the Chest X-Ray Pneumonia dataset collected from Kaggle. This dataset comprises a total of 5,863 chest X-ray images categorized into two classes: Pneumonia and Normal. Each image is of size 224 x 224 with three colour channels. To ensure a balanced representation, we divided the dataset into training, validation, and test sets with distributions of 80% training (4,690 images), 10% validation (585 images), and 10% test (588 images).

4.2 ResNET50 Results

The training and validation results for the ResNet50 model show strong performance, with high values across key evaluation metrics—accuracy, precision, and recall. Here's an analysis of the results:

Training Performance

- Loss: 0.1117 indicates a low training loss, suggesting that the model has effectively minimised the error on the training data.
- Accuracy: 96.36% shows that the model correctly classifies the majority of training samples, indicating good generalisation within the training set.
- Precision: 97.16% suggests that the model has a high true positive rate for identifying cases accurately, with fewer false positives.
- Recall: 97.97% demonstrates that the model is excellent at capturing true positives and minimising false negatives, a crucial metric in medical diagnosis where missed detections can have significant implications.

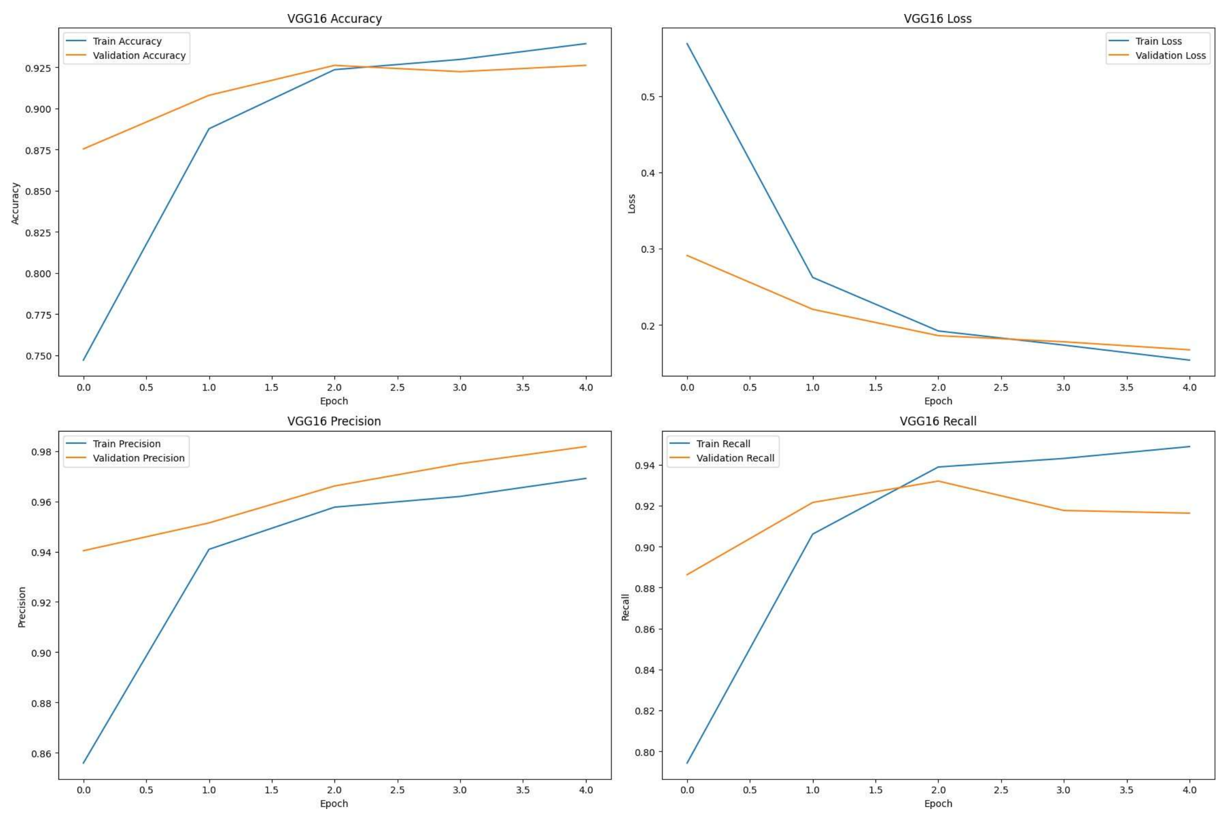
Validation Performance

- Loss: 0.1106, very close to the training loss, suggests that the model has not overfitted and retains generalisation capabilities on unseen data.
- Accuracy: 95.30% is slightly lower than the training accuracy but still very high, indicating robust performance on validation data.
- Precision: 97.23% on the validation set mirrors training precision, showing the model's consistent ability to maintain accuracy in classification.

- Recall: 96.34%, although slightly lower than the training recall, is still high and indicates reliable detection of positive cases.

Analysis Summary

The near parity between training and validation metrics shows that the ResNet50 model generalises well and isn't overfitting. Both precision and recall values are particularly high, making it suitable for applications in pneumonia detection where high precision (to avoid false positives) and high recall (to avoid missed diagnoses) are essential. The small differences between training and validation performance are expected, and they suggest that the model would likely perform well in real-world scenarios.



4.3 VGG16 Results :

The VGG16 model results demonstrate good performance, but with some notable differences compared to the ResNet50 analysis:

Training Performance

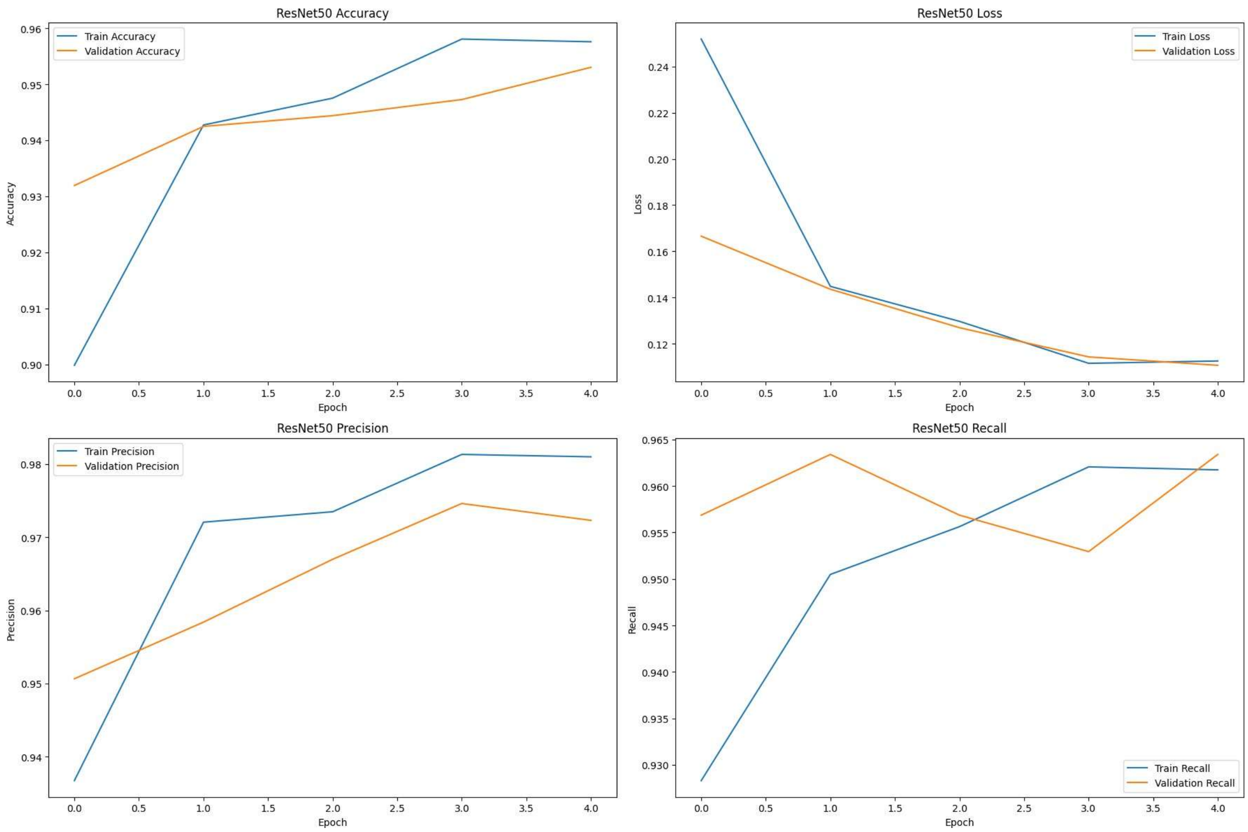
- Loss: 0.1506 is moderately low, indicating that the model performs well on the training data but with slightly more error compared to the ResNet50 results.
- Accuracy: 94.08% is high, showing that the model accurately classifies most training samples but with a slightly lower accuracy than ResNet50.
- Precision: 97.89% is excellent, highlighting that the model is effective at minimising false positives.
- Recall: 94.08% is somewhat lower, indicating that it misses a few positive cases, which is critical in medical imaging where recall is especially important.

Validation Performance

- Loss: 0.1673, a bit higher than the training loss, suggests a minor increase in error on unseen data but is not indicative of major overfitting.
- Accuracy: 92.62% is slightly lower than the training accuracy, but still high and reflects good performance on validation data.
- Precision: 98.18% indicates the model is highly precise in identifying positive cases, even better than its performance on the training set.
- Recall: 91.63% is lower than the training recall, signalling that it may occasionally miss some positive cases in the validation set.

Analysis Summary

The VGG16 model provides high precision but has a slight trade-off in recall compared to ResNet50, which could make it less ideal in cases where detecting all positive instances is paramount. While the metrics indicate the model's capability, a focus on improving recall might further optimise it for medical imaging purposes. Increasing data diversity or fine-tuning may help enhance recall and reduce the discrepancy between training and validation performance.



4.4 PneumoniaNet Results :

This model shows strong training and validation performance with high precision and recall, particularly in the validation set:

Training Performance

- **Loss**: 0.1629 indicates good minimization of error, though slightly higher than the VGG16 and ResNet50 models.
- **Accuracy**: 94.22% shows that the model effectively generalizes on the training data, achieving a high rate of correct classifications.
- **Precision**: 94.90% indicates that the model does a solid job of minimizing false positives.

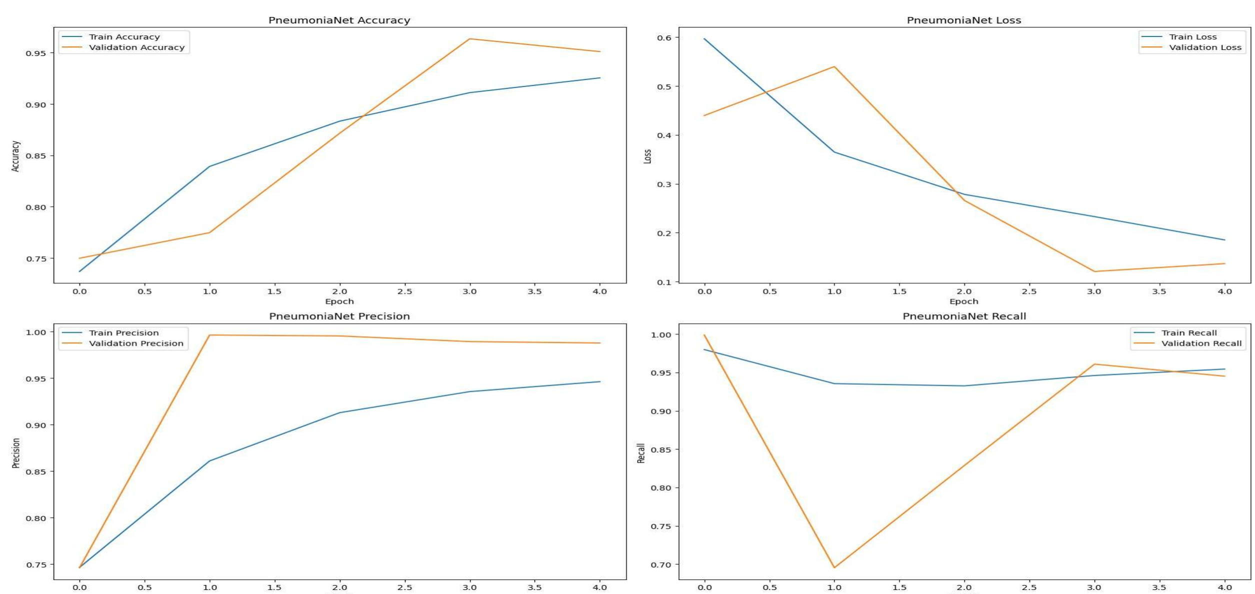
- **Recall**: 97.49% suggests that the model is highly sensitive, capturing nearly all positive instances in the training set.

Validation Performance

- **Loss**: 0.1367, which is lower than the training loss, suggests good generalisation with reduced error on unseen data.
- **Accuracy**: 95.11% is slightly higher than the training accuracy, indicating strong generalisation capabilities.
- **Precision**: 98.77% is exceptionally high, showing the model's ability to correctly identify positive cases and avoid false positives on the validation set.
- **Recall**: 94.51% is robust, suggesting the model effectively captures most positive cases without significant decline from training performance.

Analysis Summary

The model performs very well, with both high precision and recall, especially on the validation set. Lower validation loss compared to training loss might indicate an effective model architecture or beneficial data characteristics. High precision and recall make this model suitable for medical imaging scenarios where both metrics are crucial. It appears to be particularly well-balanced, with strong generalisation and minimal overfitting.



Chapter 5:Conclusion and Future work

5.1 Conclusion:

The use of VGG16 and ResNet50 as existing models provides a solid foundation for extracting diverse features from medical images, with each model contributing different strengths—VGG16's simplicity and ResNet50's deep learning capabilities. The newly proposed PneumoniaNet model enhances this by merging the features from both models and applying an attention mechanism to focus on the critical areas of the chest X-ray images, resulting in more precise detection of pneumonia.

These models are crucial in achieving our project goals by improving detection accuracy and reducing the computational cost of training. However, anticipated challenges include fine-tuning the hybrid model to avoid overfitting, managing the computational load of multi-model training, and ensuring that the attention mechanism consistently improves performance. The next steps involve testing PneumoniaNet on larger datasets, further optimizing its layers, and evaluating its real-world performance in clinical settings.

5.2 Future Scope:

While the current model has shown promising results, there are several avenues for further research and enhancements:

1. Transfer Learning:
    - Experimenting with different pre-trained models, such as DenseNet, Inception, or EfficientNet, could lead to improved performance. Each architecture has unique strengths that may yield better feature extraction capabilities.
2. Ensemble Methods:
    - Combining predictions from multiple models (ensemble learning) can reduce variance and improve predictions. Techniques like bagging or boosting could be explored to create a more robust final model.
3. Extended Dataset:
    - Incorporating additional datasets, including more diverse X-ray images from different populations and conditions, can improve the

model's robustness and ability to generalize across various demographic groups.

4. Explainability and Interpretability:
    - Integrating explainable AI techniques (e.g., Grad-CAM, SHAP values) can provide insights into model decision-making processes. This is crucial in medical applications, where understanding the rationale behind a diagnosis can enhance trust and acceptance among healthcare professionals.
5. Real-world Deployment:
    - Testing the model in real-world clinical settings can provide valuable feedback and highlight areas for further improvement. Collaborations with healthcare institutions for pilot studies can help assess the model's performance in a practical environment.
6. Website Development:

    Creating a user-friendly web application where individuals can upload their chest X-ray images and receive instant feedback on whether pneumonia is present is a crucial next step. This platform could simplify access to diagnostic tools, making it easier for users to seek preliminary evaluations. The website can include features such as:

- A straightforward interface for image uploads.
- An informative section explaining pneumonia symptoms and the importance of early detection.
- Integration of the trained model to process the uploaded images and return results efficiently.
- An option to download or share the results with healthcare providers for further consultation.

7. Detection of Pneumonia Types:

    Enhancing the model to differentiate between various types of pneumonia (e.g., bacterial, viral, fungal, or aspiration pneumonia) can provide critical insights for healthcare professionals. This can be achieved by refining the classification head of the model to include multiple output classes for each type of pneumonia, allowing for more tailored treatment strategies.

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