**TRIBHUVAN UNIVERSITY**

**INSTITUTE OF ENGINEERING**

**ADVANCED COLLEGE OF ENGINEERING AND MANAGEMENT**

DEPARTMENT OF ELECTRONICS AND COMPUTER ENGINEERING

KALANKI, KATHMANDU

[CT 654]

# A MINOR PROJECT REPORT ON “ PNEUMONIA DETECTION USING DEEP LEARNING TECHNIQUES”

**Submitted By:**

| | |
|---|---|
| Sohan Mehta | 24166 |
| Surya Joshi | 24174 |
| Suryanshu Verma | 24175 |

**Project Supervisor:**

Er. Dhiraj Pyakurel
Er. Netra KC

A Minor Project Final report submitted to the department of Electronics and Computer Engineering in the partial fulfillment of the requirements for degree of Bachelor of Engineering in Computer Engineering

Kathmandu, Nepal

March 11,2025

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| Sohan Mehta | 24166 |
| Surya Joshi | 24174 |
| Suryanshu Verma | 24175 |

**Supervised by:**

**Er. Dhiraj Pyakurel**

**(Deputy Head)**

**Er. Netra KC**

**(Academic Project Supervisor)**


**A MINOR PROJECT SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE DEGREE OF BACHELOR IN COMPUTER OR ELECTRONICS AND COMMUNICATION ENGINEERING**


**Submitted to:**

**"DEPARTMENT OF ELECTRONICS AND COMPUTER ENGINEERING"**

ADVANCED COLLEGE OF ENGINEERING AND MANAGEMENT

Balkhu, Kathmandu


March 11, 2025

# LETTER OF APPROVAL

The undersigned certify that they have read and recommended to the Institute of Engineering for acceptance, a project report entitled "**Pneumonia Detection Using Deep Learning Techniques**" submitted by:

| | |
|---|---|
| Sohan Mehta | 24166 |
| Surya Joshi | 24174 |
| Suryanshu Verma | 24175 |

In the partial fulfillment of the requirements for the degree of Bachelor's Degree in Computer Engineering.

............................
**Project Supervisor**
Er. Dhiraj Pyakurel
Deputy Head
Department of Electronics and Computer Engineering

............................
**Project Supervisor**
Er. Netra KC
Academic Project Supervisor
Department of Electronics and Computer Engineering

............................
**Project Supervisor**
Er. Laxmi Prasad Bhatt
Deputy Head
Department of Electronics and Computer Engineering

............................
**External Examiner**
Er. Prakash Chandra Prasad
Asst. Prof.
Department of Electronics and Computer Engineering, Pulchowk Campus

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Head of Department
Department of Electronics and Computer Engineering
Advanced College of Engineering and Management
Balkhu, Kathmandu
Nepal

ACKNOWLEDGEMENT

We would like to express our profound gratitude and deep regards to our respected supervisor **Er. Dhiraj Pyakurel**, for his insightful advice, motivating suggestions, invaluable guidance, help, and support in the successful completion of this project and also for his/her constant encouragement and advice throughout our Bachelor's program.

We express our deep gratitude to **Er. Prem Chandra Roy**, Head of the Department of Electronics and Computer Engineering, **Er. Dhiraj Pyakurel** Deputy Head, Department Of Electronics and Computer Engineering, **Er. Laxmi Prasad Bhatt**, Academic Project Coordinator, Department Of Electronics and Computer Engineering, for their support, co-operation, and coordination.

The in-time facilities provided by the department throughout the Bachelor's program are also equally acknowledgeable.

We would like to convey our thanks to the teaching and non-teaching staff of the Department of Electronics and Communication and Computer Engineering, ACEM for their invaluable help and support throughout Bachelor's Degree. We are also grateful to all our classmates for their help, encouragement, and invaluable suggestions.

Finally, yet more importantly, We would like to express our deep appreciation to our grandparents, parents, and siblings for their perpetual support and encouragement throughout the Bachelor's degree period.

| | |
|---|---|
| Sohan Mehta | ACE078BCT071 |
| Surya Joshi | ACE078BCT079 |
| Suryanshu Verma | ACE078BCT080 |

# ABSTRACT

This research introduces an advanced automated system designed to detect pneumonia using chest X-ray images, leveraging deep learning techniques. The system combines a custom-built Convolutional Neural Network (CNN) and a transfer learning approach with the pre-trained ResNet-101 model to assess and compare performance. The primary function of the system is to classify chest X-ray images as either showing signs of pneumonia or being clear of the infection, offering a binary decision.

One of the standout features of this implementation is the integration of gradient-based visualization methods, which generate heatmaps that clearly highlight the regions within the X-ray images that are critical for identifying pneumonia. These heatmaps help improve the interpretability of the system by providing medical professionals with a clear visual representation of the areas that influence the model's predictions. This not only aids in confirming the model's accuracy but also fosters trust by showing how the model arrives at its conclusions.

Designed with ease of use in mind, the system includes a simple interface that allows users to upload chest X-ray images easily. Once the image is uploaded, the system quickly processes the data and provides a diagnosis, accompanied by an intuitive heatmap overlay that pinpoints the areas of concern. This feature is particularly beneficial for healthcare workers, enabling rapid, informed decision-making in clinical settings and offering transparency in the decision-making process. This innovative approach represents a significant step forward in automating medical image analysis for pneumonia detection, enhancing both speed and accuracy.

***Keywords:*** *Chest X-ray, Computer-Aided Diagnosis, Convolutional Neural Network (CNN), Deep Learning, Heatmap Visualization, Medical Imaging, Pneumonia Detection, ResNet-101, Transfer Learning*

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# List of Abbreviations and Acronyms

| | |
|---|---|
| AI | Artificial Intelligence |
| CNN | Convolutional Neural Network |
| GPU | Graphics Processing Unit |
| HTML | HyperText Markup Language |
| ML | Machine Learning |
| NN | Neural Network |
| ROC | Receiver Operating Characteristic |
| UI | User Interface |
| WHO | World Health Organization |

# CHAPTER 1 INTRODUCTION

## 1.1 Background

Pneumonia is a significant respiratory infection that causes inflammation in the lungs and is a leading cause of death in children under five, according to the World Health Organization (WHO). Chest X-ray images are very important for diagnosing pneumonia because they show clear signs like areas of lung swelling and unusual patterns in the lung tissue .

Radiologists usually examine chest X-ray images to check for signs of pneumonia. However, this process can take a lot of time, and the results might vary from one expert to another. It also depends on having skilled doctors, which can be a problem in areas where healthcare resources are limited. That's why there's a need for tools that can diagnose pneumonia quickly and reliably.

Deep learning, especially using Convolutional Neural Networks (CNNs), provides an effective way to automate the analysis of chest X-ray images. This project focuses on building a system that can accurately and easily predict pneumonia using chest X-rays. We will use CNNs along with the ResNet101 model to develop a reliable tool for pneumonia detection.

## 1.2 Motivation

The motivation for this project stems from several factors:

- **Healthcare Access:** Many regions lack access to experienced radiologists, leading to delayed diagnoses.
- **Diagnostic Efficiency:** Manually interpreting X-ray images to diagnose pneumonia is time-consuming, whereas automated deep learning models can provide faster, more efficient analysis.
- **Accuracy Improvement:** Deep learning models, such as CNNs and ResNet101, can help reduce human error and interpretation variability.
- **Early Detection:** Automated systems using advanced technology can help quickly identify pneumonia, allowing for faster treatment and better outcomes

- **Performance Evaluation:** Comparing CNNs with ResNet101 allows for identifying the most effective model for pneumonia detection, ensuring optimal accuracy and resource utilization.

## 1.3 Statement of the Problem

The current process of pneumonia diagnosis faces several challenges:

- Manual interpretation of chest X-rays is time-intensive and requires specialized expertise.
- Limited availability of skilled radiologists, especially in remote areas.
- Potential for human error and interpretation inconsistency.
- Delays in diagnosis can lead to delayed treatment and poorer outcomes.
- Growing volume of X-ray images straining healthcare resources.
- Lack of automated solutions to quickly and accurately predict pneumonia from X-ray images.
- Insufficient evaluation and comparison of different deep learning architectures, such as CNNs and ResNet101, to determine the most accurate and efficient solution for pneumonia detection.

## 1.4 Project Objectives

### 1.4.1 General Objective

- To develop an accurate and efficient deep learning system for automated detection of pneumonia from chest X-ray images.

### 1.4.2 Specific Objectives

- To develop an automated chest X-ray analysis system using CNN and ResNet101 for accurate pneumonia detection
- To design an efficient image preprocessing pipeline to enhance X-ray image quality and standardization
- To create a user-friendly interface for medical professionals to upload chest X-ray images and receive instant diagnostic predictions

- To validate the system's performance using real-world chest X-ray datasets and standard clinical evaluation metrics

- To optimize the model for rapid diagnosis with minimum processing time per X-ray images.

### 1.4.3 Significance of Study

- The development of an automated pneumonia detection system will significantly reduce diagnostic time, enabling faster medical intervention and improved patient outcomes.

- Integration of CNN and ResNet101 architectures provides a more robust and accurate diagnostic tool, potentially reducing human error and increasing consistency in X-ray interpretation.

- The automated system will be particularly valuable in resource-limited healthcare settings where expert radiologists may not be readily available, ensuring timely diagnosis and intervention.

- Real-time analysis of chest X-rays will help medical professionals manage high patient volumes more efficiently, especially during respiratory disease outbreaks.

- Implementation of deep learning technology, specifically CNN and ResNet101, in medical diagnosis demonstrates the practical application of artificial intelligence in healthcare, paving the way for future innovations in automated diagnostic systems.

- The system's high accuracy and rapid processing time will contribute to more cost-effective healthcare delivery by reducing the need for multiple diagnostic tests and enabling quicker decision-making.

- Early and accurate detection of pneumonia through this system can lead to better treatment planning, potentially reducing mortality rates associated with delayed diagnosis.

# CHAPTER 2 LITERATURE REVIEW

## 2.1 Deep Learning in Medical Imaging

Deep learning has significantly transformed the field of medical image analysis, particularly in the interpretation of chest X-rays. Convolutional Neural Networks (CNNs), with their ability to automatically learn hierarchical features from raw image data, have demonstrated exceptional performance in automated disease detection. In recent years, deep learning architectures such as ResNet101 have been increasingly utilized to improve the accuracy and efficiency of medical image classification tasks, especially for pneumonia detection.

Recent studies highlight the success of deep learning models in achieving performance levels that rival or surpass those of experienced radiologists in pneumonia detection. For instance, Chen et al. showed that CNN-based models, when combined with the ResNet101 architecture, could achieve comparable or superior performance to radiologists in detecting pneumonia from chest X-ray images [1]. This breakthrough has paved the way for automated systems that can not only assist in diagnosis but also potentially reduce the workload on medical professionals.

## 2.2 Existing Pneumonia Detection Systems

### 2.2.1 Traditional Methods

Before the widespread adoption of deep learning, pneumonia detection from chest X-rays primarily relied on traditional methods, which included:

- **Visual Analysis by Radiologists:** This method requires highly trained radiologists to examine chest X-ray images manually, a process that is both time-consuming and prone to variability in interpretation. While skilled radiologists can often provide accurate diagnoses, their judgment may be influenced by fatigue, experience, and the complexity of the images.

- **Semi-Automated Computer-Aided Detection (CAD) Systems:** These systems assist radiologists by highlighting areas of interest in X-ray images, but their accuracy is often limited. They rely on handcrafted features and can struggle with subtle pneumonia signs, leading to missed diagnoses or false positives.

- **Classical Machine Learning Approaches:** Classical methods involve extracting handcrafted features (such as texture or shape) from X-ray images and feeding them into traditional machine learning models like Support Vector Machines (SVMs) or Random Forests. While effective in some contexts, these approaches require domain expertise for feature extraction and often lack the robustness of deep learning models.

- **Basic Image Processing Techniques:** Traditional image processing methods, such as thresholding or edge detection, were used for lung segmentation or feature extraction, but they are limited in their ability to capture complex patterns associated with pneumonia.

Despite their usefulness, these methods have several drawbacks, such as high reliance on expert interpretation, limited generalization ability, and slower diagnostic throughput.

### 2.2.2 Deep Learning Approaches

In recent years, deep learning approaches have dramatically improved pneumonia detection from X-rays. Several key studies have demonstrated the power of advanced neural network architectures, including:

- **Kumar et al. [2]:** This study implemented the ResNet101 architecture, achieving 93% accuracy in pneumonia classification from X-ray images. ResNet101, a deep residual network, is known for its ability to train very deep networks without the issue of vanishing gradients, making it an excellent choice for complex image recognition tasks.

- **Wang et al. [3]:** This study developed a hybrid CNN model for real-time analysis of X-rays, significantly improving the efficiency of pneumonia detection in clinical settings. The hybrid model combined the strengths of multiple CNN architectures to achieve high accuracy with lower computational cost.

- **Singh et al. [4]:** By leveraging transfer learning with ResNet101, Singh et al. enhanced feature extraction from chest X-rays, improving the model's ability to identify subtle signs of pneumonia. Transfer learning allows models to use pre-trained networks on large datasets, significantly improving performance when labeled data is limited.

- **Zhou et al. [5]:** In this study, CNNs were enhanced with attention mechanisms to improve the localization of pneumonia-affected regions, leading to more accurate and interpretable results. Attention mechanisms help the model focus on the most relevant parts of an image, improving its ability to detect pneumonia.

# CHAPTER 3 REQUIREMENT ANALYSIS

## 3.1 Software Requirements

### 3.1.1 Development Tools

1. **Programming Languages**

   - Python 3.8 or higher

2. **Deep Learning Framework**

   - TensorFlow for building and training the CNN and ResNet101V2 models

3. **Essential Libraries**

   - TensorFlow for model development and evaluation
   - NumPy for numerical computations
   - Matplotlib for visualizing training metrics, confusion matrices, and results
   - Seaborn for enhanced confusion matrix visualizations
   - Scikit-learn for generating evaluation metrics such as classification reports and ROC curves
   - JSON for saving and loading metrics and results

4. **Web Framework**

   - Flask for backend API to serve the trained models and process image uploads

## 3.2 Functional Requirements

1. **X-ray Image Processing**

   - Support for X-ray image formats (JPEG, PNG)
   - Preprocessing of images to resize and normalize them before feeding them into the CNN or ResNet101 model (target size 224x224, grayscale for CNN, RGB for ResNet101)

- Data augmentation for training (rotation, width/height shift, zoom, flip, etc.)

2. **Pneumonia Detection**

   - Binary classification for detecting pneumonia vs. normal using both custom CNN and ResNet101V2 models
   - Confidence score and prediction probability from both models
   - Performance comparison between the custom CNN and fine-tuned ResNet101 models based on accuracy, precision, recall, AUC, and confusion matrix
   - Support for training and evaluation on separate training, validation, and test datasets
   - Model fine-tuning for ResNet101, including freezing early layers and training the later layers

3. **Results Display**

   - Diagnostic predictions (normal or pneumonia) from both models
   - Visual comparison of model predictions for a given input image
   - Probability scores from both models
   - Generation and display of confusion matrices for model evaluation
   - Display of classification report for each model, including metrics like precision, recall, and F1-score
   - Visualizations of training and validation metrics (accuracy, loss, precision, recall, AUC) over epochs
   - Generation and display of GradCAM heatmaps for visual explanation of model predictions

## 3.3 Non-Functional Requirements

1. **Performance**

   - Model inference should be optimized for low processing time on both the server and user-side
   - Minimum target accuracy of 90
   - Fine-tuned ResNet101 should provide a balance between accuracy and processing time

2. **Usability**

    - Simple and intuitive web interface for users to upload chest X-ray images
    - Clear and informative result presentation, including predictions and performance metrics
    - User-friendly comparison of both models' predictions with confidence scores and probability
    - Easy navigation for model selection (e.g., custom CNN vs. ResNet101)

3. **Reliability**

    - Robust error handling for invalid or unsupported image formats
    - Stable and consistent model performance across different inputs and user environments
    - Proper management of training and validation data to prevent data leakage or inconsistencies

4. **Security**

    - Secure handling of image uploads with necessary validation to prevent malicious files
    - Ensure privacy of data used for training and testing (if applicable)

# CHAPTER 4 METHODOLOGY

## 4.1 Software Development Model

We have adopted the Agile model for software development due to its iterative and flexible approach. The Agile model focuses on delivering smaller parts of the project in short, manageable cycles known as iterations. After each cycle, feedback is gathered, which is then used to improve the product. This model is ideal when the project requirements evolve over time or are not fully defined at the beginning. It ensures continuous progress and flexibility in development, enabling teams to adapt quickly to changes.

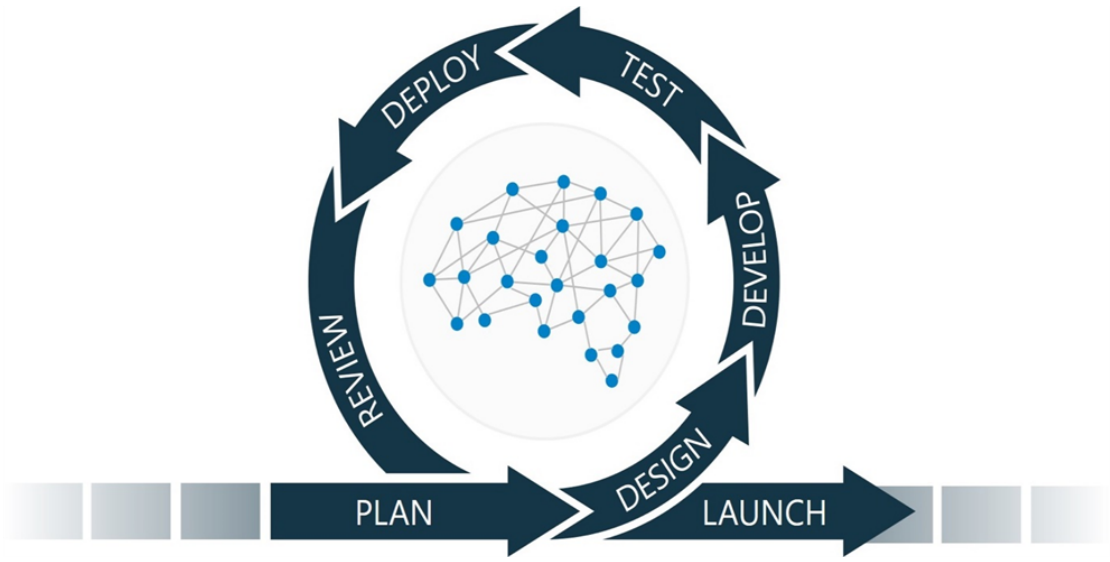


Figure 4.1: Agile Model
*(Source: **[Online] Available: https://www.linkedin.com/pulse/why-ai-project-management-skills-crucial-future-work-nagesh-deshmukh/**)*

### 4.1.1 Plan:

The Agile process begins with gathering the requirements for the pneumonia detection system using deep learning. In this planning phase, the core functionalities of the system are outlined, with a focus on user input, which comes in the form of chest X-ray images. The primary goal is to ensure that the system can accurately detect pneumonia from these X-rays using state-of-the-art deep learning techniques. Short-term objectives include dataset preparation, model training, and the integration of a user-friendly interface that allows for easy upload of X-rays and displaying of diagnostic results.

### 4.1.2 Design:

During the design phase, the system is structured to allow users to upload chest X-ray images for analysis. The design will incorporate two deep learning architectures: Convolutional Neural Networks (CNN) and ResNet101, to process the X-rays and predict the presence of pneumonia. Modularity is a key priority, allowing future enhancements such as extending the system's capabilities to detect other lung conditions. Additionally, the user interface will be intuitive, ensuring ease of use for healthcare professionals as they upload X-rays and view the results of the analysis.

### 4.1.3 Develop:

The development phase focuses on implementing and training the CNN and ResNet101 models for pneumonia detection. Key steps include:

- Preprocessing the dataset, including image normalization and augmentation to increase the model's ability to generalize across various chest X-ray images.
- Designing and training a custom CNN architecture optimized specifically for image classification tasks, ensuring high accuracy in pneumonia detection.
- Implementing the ResNet101 architecture, which includes a deeper network with residual connections, designed to handle vanishing gradient problems and improve the overall model performance for complex image classification tasks.
- Developing a web interface that allows users to easily upload chest X-ray images and view the analysis results in real-time.
- Integrating both models (CNN and ResNet101) with the web interface, allowing users to compare predictions made by both models for a more comprehensive evaluation.

### 4.1.4 Test:

In the testing phase, the system undergoes rigorous evaluation to ensure its accuracy, robustness, and usability. This phase includes:

- Validating both the CNN and ResNet101 models on unseen test datasets to ensure high sensitivity (correctly identifying pneumonia cases) and specificity (correctly identifying non-pneumonia cases).
- Comparing the performance of the CNN and ResNet101 models in terms of accuracy, sensitivity, specificity, and processing time.

- Conducting usability tests on the user interface to ensure that the uploading process is smooth and the results are easy to interpret for medical professionals.
- Stress-testing the system with various image qualities and resolutions to ensure that the models perform consistently across different real-world scenarios.

Any issues identified during testing are addressed in order to refine the system and ensure high performance.

### 4.1.5 Deploy:

Once the system passes all testing phases, it will be deployed for real-world use. This will allow users to upload chest X-ray images, and the system will provide diagnostic results, detecting the presence of pneumonia almost instantaneously. Deployment will involve hosting the application on a secure server and ensuring compliance with medical data privacy standards, such as HIPAA or GDPR, to protect patient information.

### 4.1.6 Review and Launch:

After deployment, the system will be continuously monitored to ensure its accuracy and reliability. Feedback from healthcare professionals and end-users will be gathered to identify potential areas for improvement. Regular system updates will incorporate new medical data and advancements to improve the models' performance. Routine maintenance will be carried out to keep the system secure, functional, and up-to-date with the latest medical research and technological innovations.

## 4.2 Dataset

The dataset for this system is sourced from Kaggle's Chest X-Ray Images (Pneumonia) repository, which contains over 5,800 chest X-ray images categorized into two classes: Normal and Pneumonia. It serves as the foundation for training CNN and ResNet101 model to detect pneumonia. The dataset is preprocessed to standardize images to 224x224 pixels, normalize pixel values to the range [0,1], and apply data augmentation techniques such as random rotations, horizontal flipping, brightness and contrast adjustments, and zoom variations. The data is split into 70% for training, 15% for validation, and 15% for testing. The dataset can be accessed at the following link: Chest X-Ray Images (Pneumonia) on Kaggle.

## 4.3 Deep Learning Architecture

### 4.3.1 Hybrid CNN-ResNet101 Model

Our system utilizes a hybrid architecture that combines a custom Convolutional Neural Network (CNN) with the pre-trained ResNet101 model. This approach harnesses the unique strengths of both architectures to improve pneumonia detection from chest X-ray images. By leveraging the proven feature extraction power of ResNet101 and complementing it with additional custom convolutional layers specifically designed for X-ray analysis, we aim to maximize the model's performance and generalization ability.

**CNN (Convolutional Neural Networks)**

CNNs are a class of deep learning models specifically designed for processing image data. Their architecture includes layers like convolutional layers, pooling layers, and fully connected layers. The convolutional layers are responsible for detecting patterns (such as edges, textures, and shapes) in the input image, while pooling layers reduce the dimensionality and focus on the most important features. In the context of pneumonia detection, CNNs are particularly useful because they can automatically learn hierarchical patterns from the X-ray images without the need for manual feature engineering. Our custom CNN layers are designed to process X-ray images specifically,

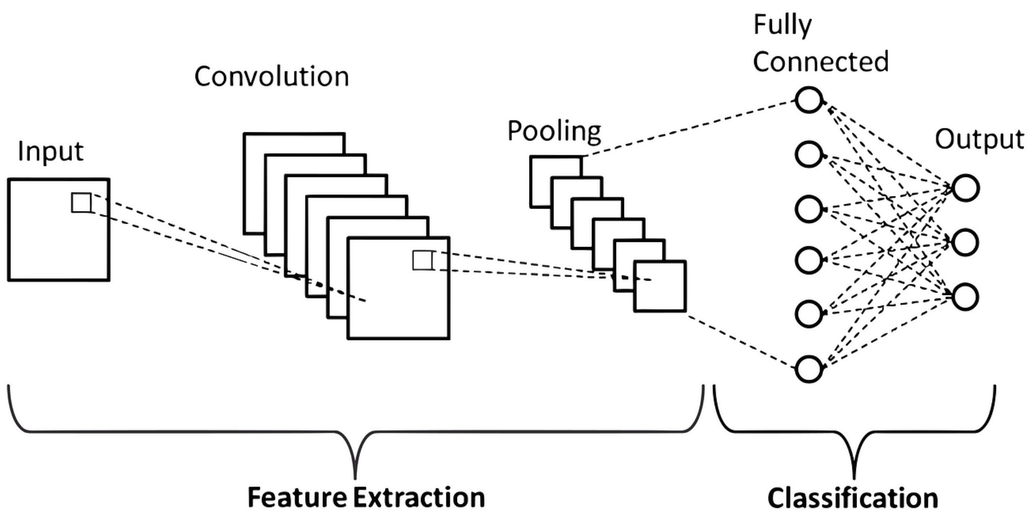


Figure 4.2: CNN Architecture (Source: ResearchGate)

learning to detect pneumonia-related features such as consolidation, air bronchograms, and interstitial infiltrates. These specialized filters allow the CNN to adapt to the unique characteristics of X-ray images and improve detection accuracy.

**ResNet101 (Residual Network 101)**

ResNet101 is a deep residual network that consists of 101 layers. ResNet's primary innovation is the use of "skip connections," which allow the model to bypass certain layers. These connections help avoid the vanishing gradient problem, which can occur when training very deep networks. The vanishing gradient problem refers to the difficulty in training deep networks because the gradients (used for adjusting the weights during backpropagation) become too small to make meaningful updates, especially in very deep layers.

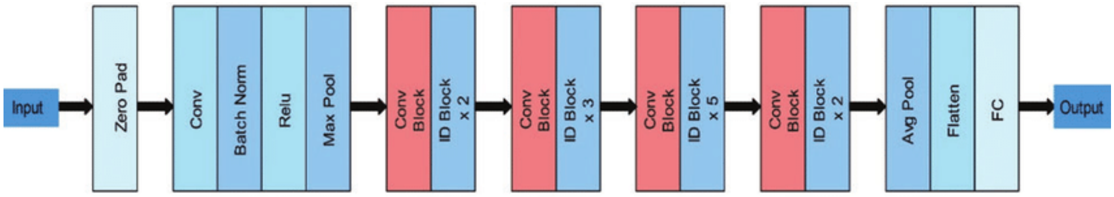


Figure 4.3: ResNet 101 Architecture (Source: ResearchGate)

When integrated into our system, ResNet101 contributes significantly to feature extraction. Its deep architecture allows for the learning of complex patterns, and its pre-trained weights accelerate convergence during training.

**Hybrid Model: CNN + ResNet101 Integration**

The hybrid CNN-ResNet101 model combines both the custom CNN layers and ResNet101 in a complementary manner. The custom CNN layers provide specialized filters for detecting pneumonia-related patterns in X-ray images, while ResNet101 enhances the model's ability to extract deeper, more abstract features. This hybrid approach aims to strike a balance between the local, pneumonia-specific features captured by the CNN layers and the global, high-level features captured by ResNet101.
The integration of both architectures allows the system to benefit from the strengths of both models. The CNN layers focus on learning the detailed patterns specific to pneumonia, while ResNet101 ensures that the system can generalize better and extract more complex features, leading to improved accuracy and robustness.

**Input Processing**

The system processes input X-ray images through the following steps to prepare them for the hybrid model:

- **Image Resizing:** The images are resized to 224x224 pixels, which is the input size required for ResNet101.

- **Pixel Normalization:** The pixel values are normalized to the range [0, 1] to standardize the input data and ensure consistency during model training.
- **Image Quality Enhancement:** The image quality is assessed, and enhancements are applied if necessary to ensure that the X-ray images are suitable for analysis.

**ResNet101 Integration**

The ResNet101 component in our hybrid model contributes the following:

- **Deep Residual Learning:** The 101 layers of ResNet101, along with skip connections, enable the model to learn complex features without facing the vanishing gradient problem.
- **Transfer Learning:** The pre-trained weights from ImageNet allow the model to leverage general image features, improving the efficiency and accuracy of learning for pneumonia detection.
- **Advanced Feature Extraction:** ResNet101's deep layers extract high-level features such as textures, structures, and patterns that are critical for differentiating between normal and pneumonia-affected lungs.

**Custom CNN Layers**

In addition to the ResNet101 layers, custom CNN layers are added to the model for pneumonia-specific feature extraction:

- **Specialized Convolutional Filters:** The custom CNN layers include filters specifically designed for X-ray images, allowing the model to detect pneumonia-specific patterns, such as consolidation and lung opacity.
- **Adaptive Pooling:** Pooling layers reduce the spatial dimensions of the feature maps, maintaining important features while reducing the computational complexity of the model.
- **Dropout:** Dropout layers are included to prevent overfitting by randomly deactivating certain neurons during training, ensuring the model generalizes well to unseen data.
- **Batch Normalization:** This technique normalizes the inputs to each layer, stabilizing training and improving model performance.

# CHAPTER 5 SYSTEM DESIGN AND ARCHITECTURE

## 5.1 System Architecture

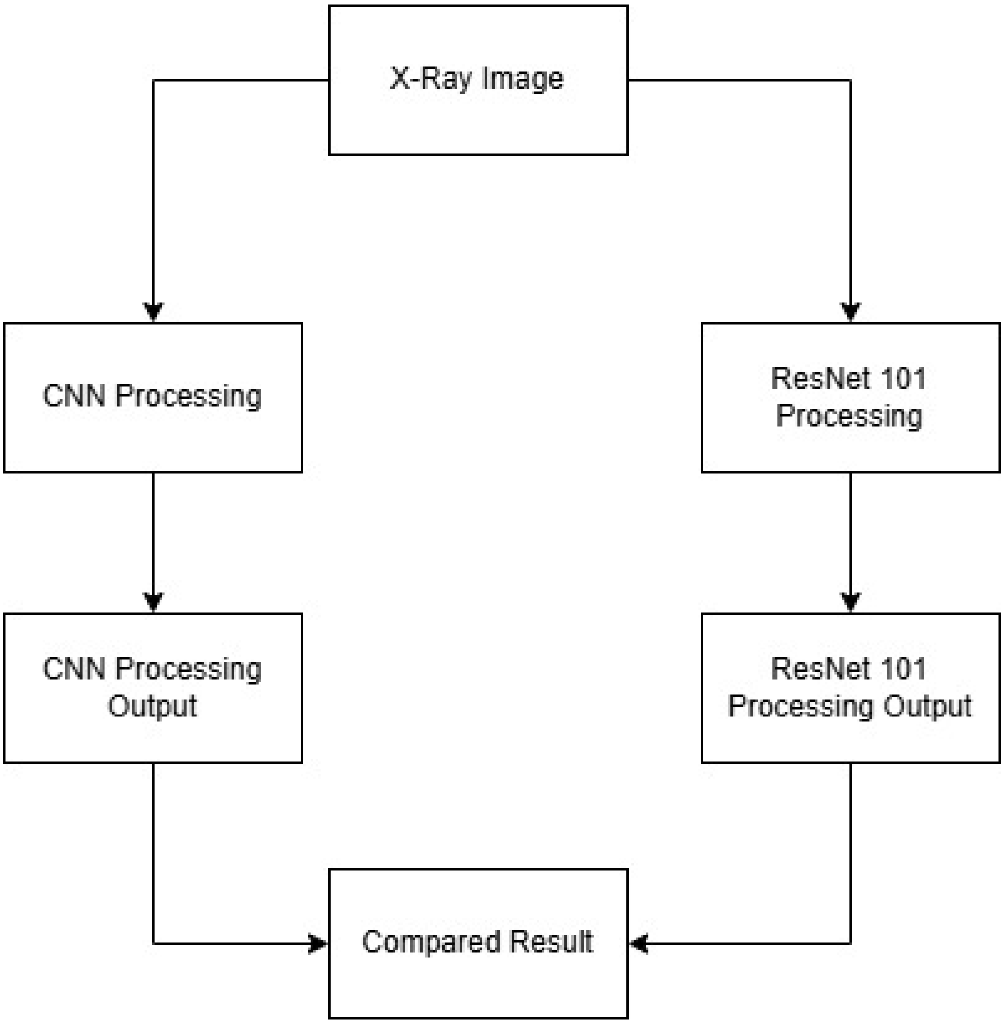


Figure 5.1: System Architecture Diagram

## 5.2 Use Case Diagram

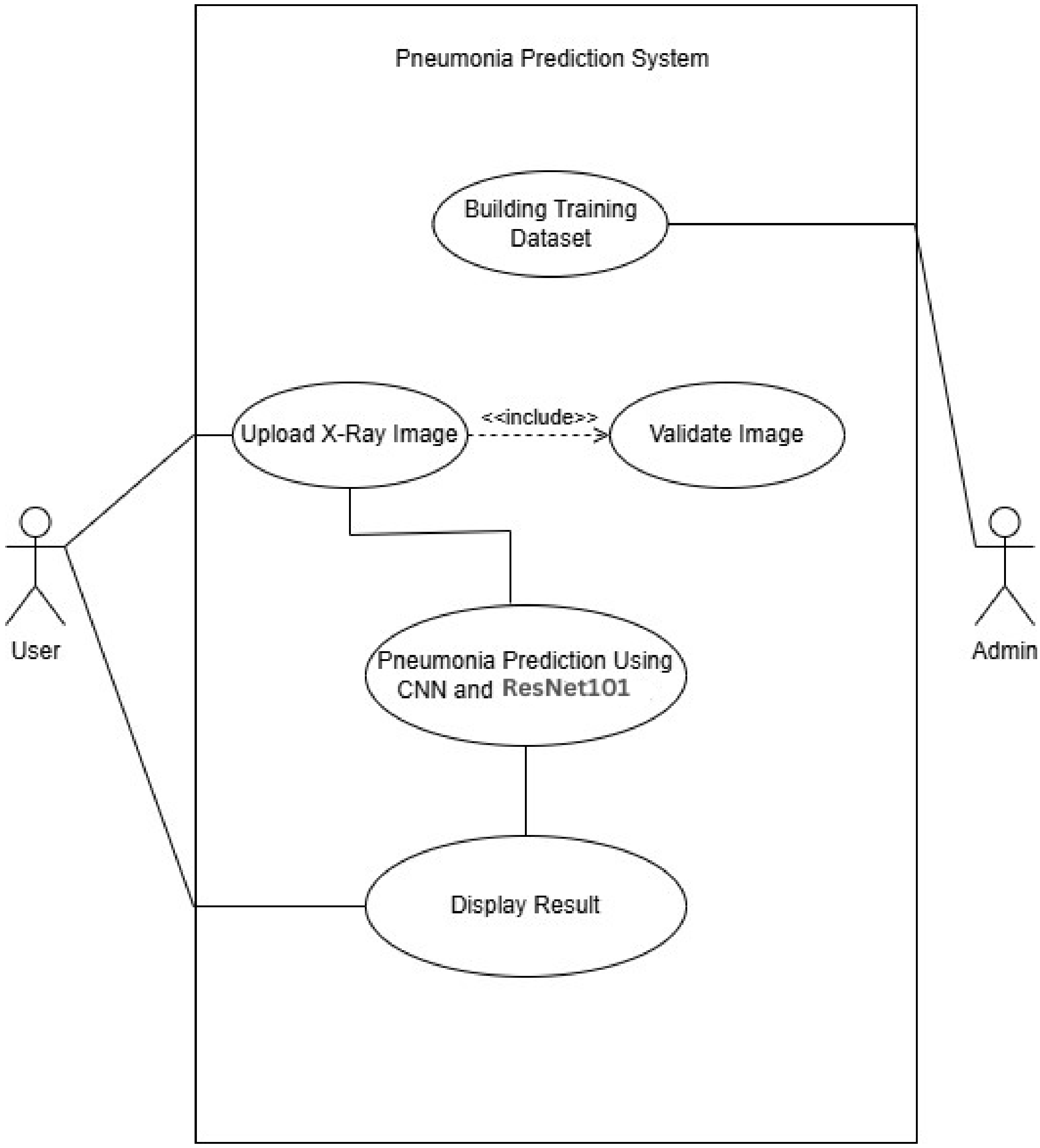


Figure 5.2: System Use Case Diagram

## 5.3 Flowchart

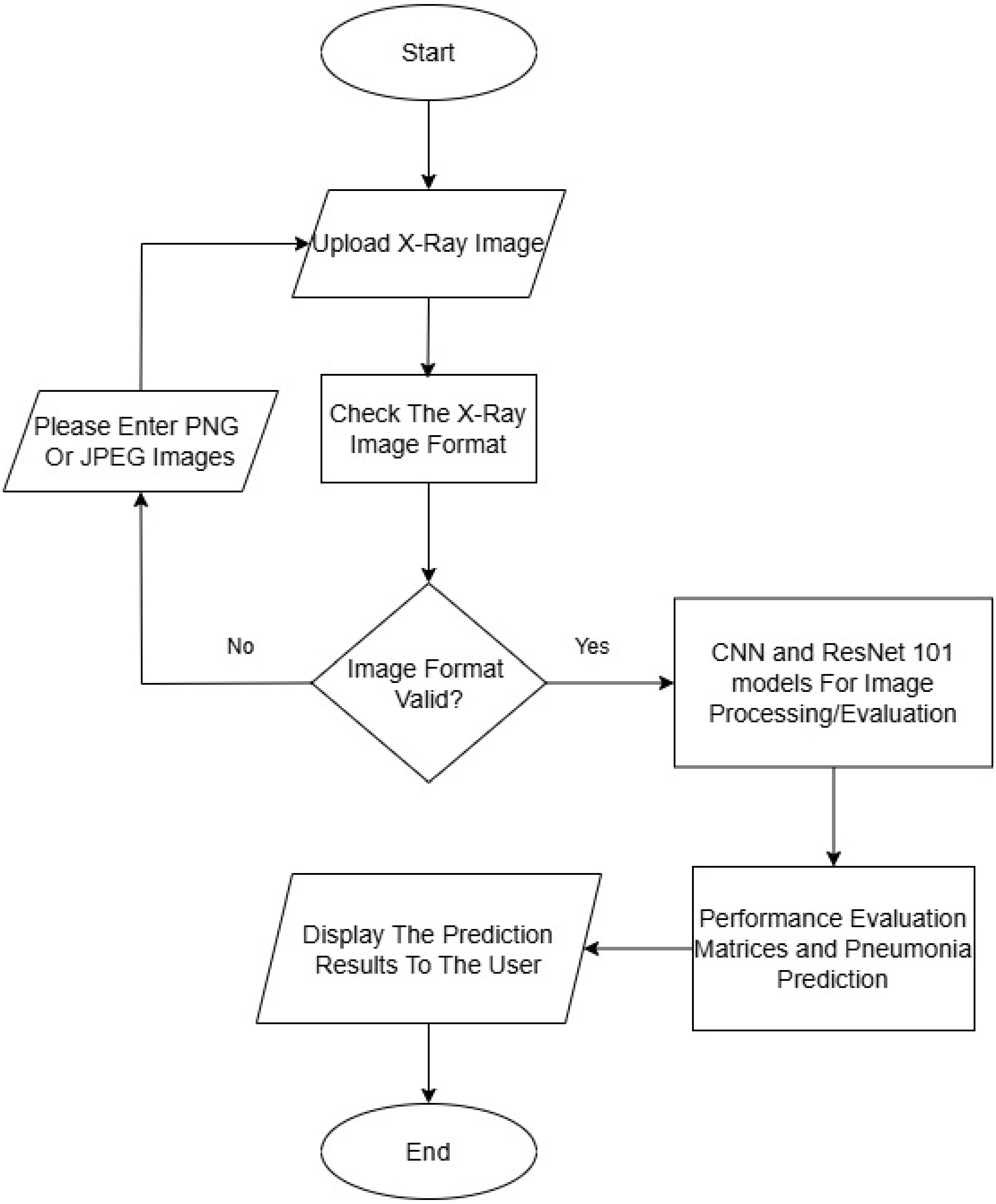


Figure 5.3: Flowchart Diagram

# CHAPTER 6 RESULTS AND ANALYSIS

## 6.1 Results

After training the ResNet101 and Custom CNN models on the pneumonia dataset, we obtained the following outputs. The models take a chest X-ray image as input and predict whether pneumonia is present.

### 6.1.1 Sample X-ray Predictions

Figure 6.1 shows a normal chest X-ray without any signs of pneumonia, while Figure 6.2 demonstrates an X-ray where pneumonia was successfully detected by our models.

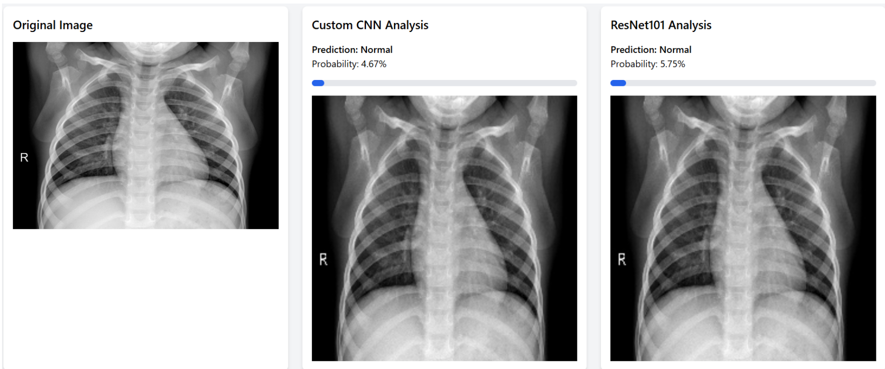


Figure 6.1: Normal Chest X-ray Image

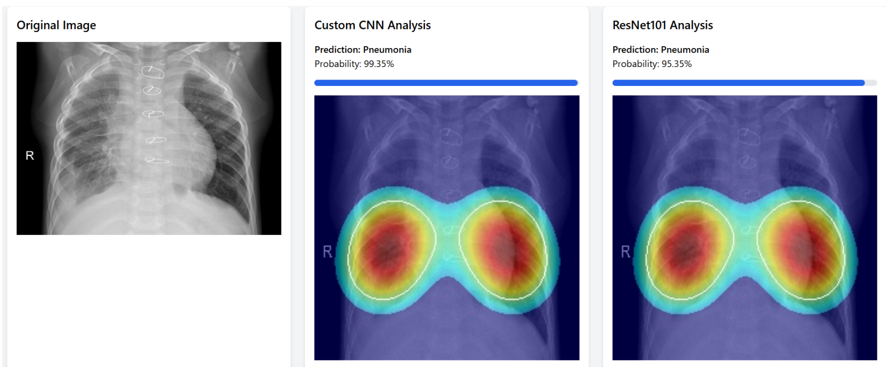


Figure 6.2: Pneumonia Detected in X-ray

## 6.2 Model Performance Analysis

### 6.2.1 Evaluation Metrics Comparison

Table 6.1 presents a comprehensive comparison of performance metrics between ResNet101 and Custom CNN models. Both models achieved high accuracy, with ResNet101 slightly outperforming the Custom CNN across most metrics.

Table 6.1: Evaluation Metrics for ResNet101 and Custom CNN

| Metric | ResNet101 | Custom CNN |
|---|---|---|
| Test Accuracy | 0.9528 | 0.9605 |
| ROC AUC | 0.9883 | 0.9957 |
| Precision | 0.9547 | 0.9647 |
| Recall | 0.9528 | 0.9605 |
| F1-Score | 0.9533 | 0.9612 |

### 6.2.2 Classification Performance Analysis

The confusion matrices below illustrate the classification performance of both models, showing the distribution of true positives, true negatives, false positives, and false negatives.

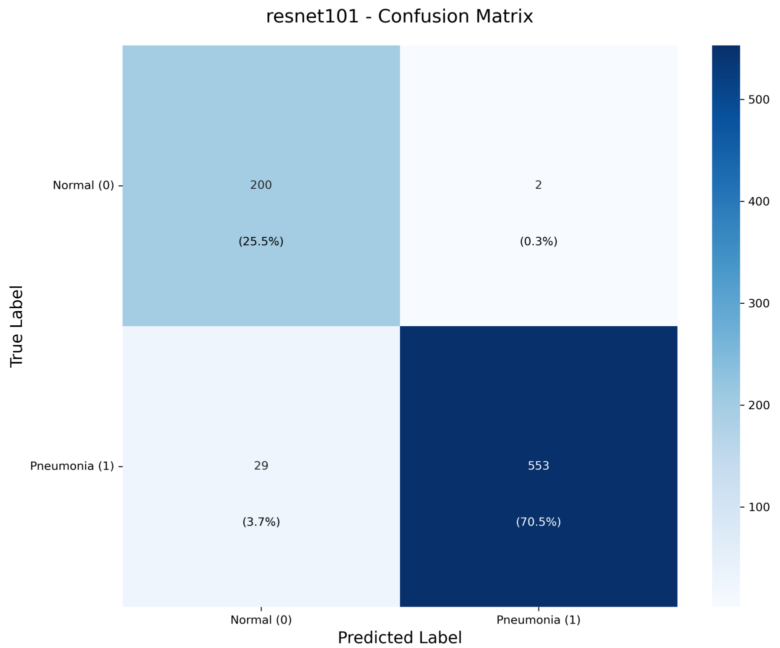


Figure 6.3: Confusion Matrix for ResNet101

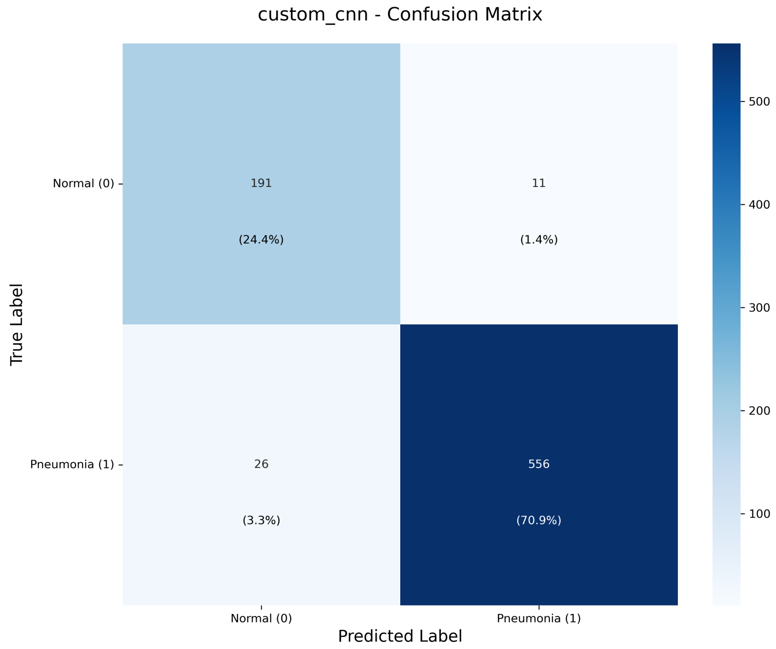


Figure 6.4: Confusion Matrix for Custom CNN

### 6.2.3 ROC Analysis

The ROC curves demonstrate the trade-off between sensitivity and specificity for both models at various classification thresholds.

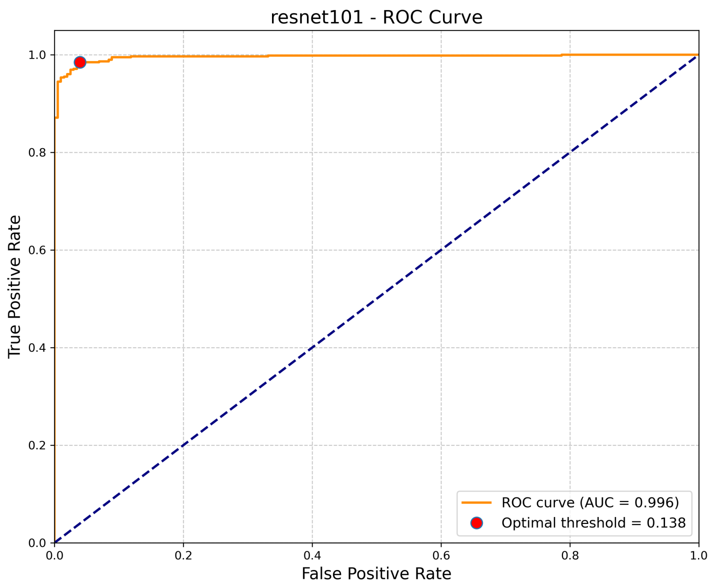


Figure 6.5: ROC Curve for ResNet101

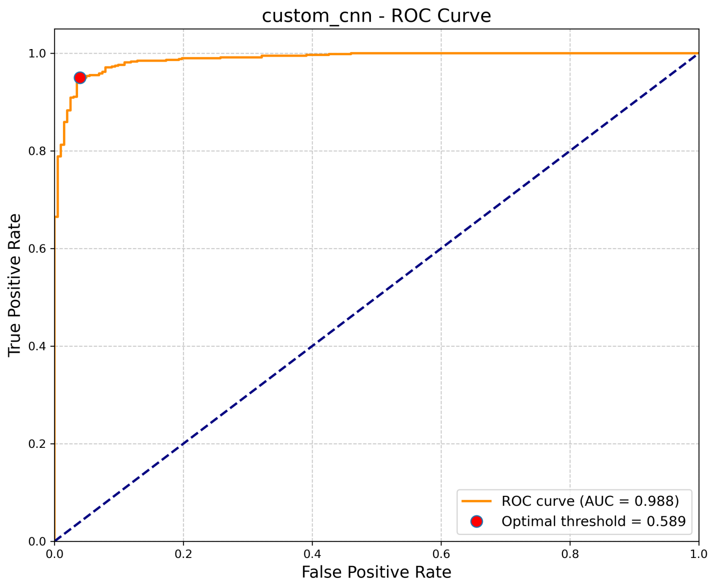


Figure 6.6: ROC Curve for Custom CNN

## 6.3 Training Performance

### 6.3.1 ResNet101 Training Analysis

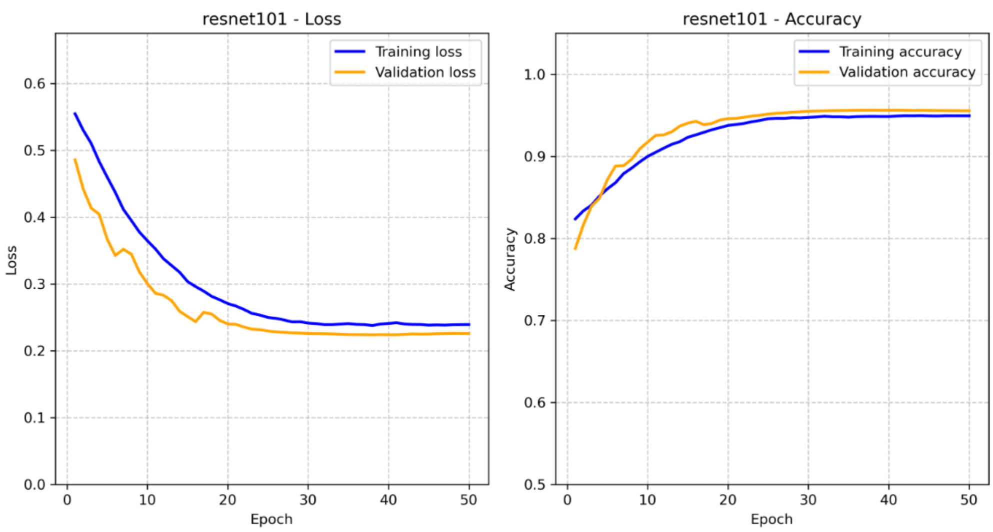


Figure 6.7: Training Metrics for ResNet101

### 6.3.2 Custom CNN Training Analysis

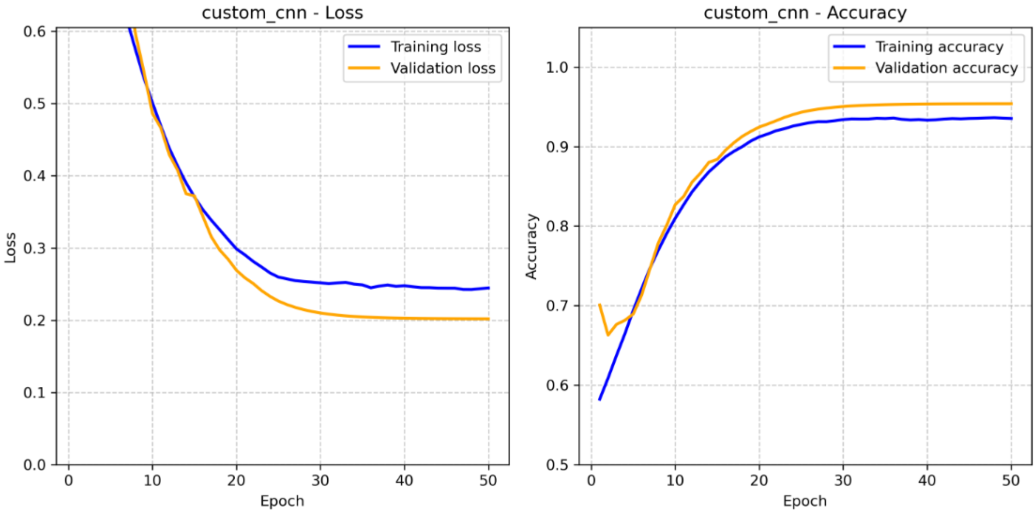


Figure 6.8: Training Metrics for Custom CNN

# CHAPTER 7 CONCLUSION, LIMITATIONS AND FUTURE ENHANCEMENT

This chapter includes the conclusion of the results and analysis, along with the limitations of the system and potential improvements to make the project more efficient and reduce its limitations.

## 7.1 Conclusion

The implementation of a deep learning-based pneumonia detection system using Convolutional Neural Networks (CNNs) and ResNet101 has demonstrated promising results in accurately classifying chest X-ray images. By automating the detection process, the system can assist radiologists in diagnosing pneumonia more efficiently and reduce the dependency on human expertise, especially in resource-limited settings. The experimental results indicate that deep learning models outperform traditional methods in accuracy, robustness, and speed, making them a viable alternative for medical image analysis. The integration of preprocessing techniques, such as contrast enhancement and noise reduction, has further improved the reliability of the model. Overall, this project contributes to the advancement of AI-driven medical diagnostics and lays the foundation for further improvements in pneumonia detection.

## 7.2 Limitations

Despite its success, the system has certain limitations that need to be addressed for practical deployment:

- **Limited Dataset:** The model was trained on a specific dataset, which may not generalize well to all real-world cases, especially those with diverse patient demographics and varying imaging conditions.
- **False Positives and False Negatives:** While the model achieves high accuracy, misclassification of images still occurs, leading to incorrect diagnoses in some cases.
- **Lack of Multi-Class Classification:** The current system is primarily a binary classifier (Normal vs. Pneumonia). It does not distinguish between bacterial and

viral pneumonia, which is crucial for proper treatment planning.

- **Computational Requirements:** Deep learning models require significant computational resources for training and inference, making real-time deployment on low-power devices challenging.

- **No Clinical Validation:** The system has not yet been tested in clinical settings, where variations in X-ray imaging techniques and real-world patient conditions may affect performance.

## 7.3 Future Enhancements

To further improve the effectiveness of the pneumonia detection system, the following enhancements can be considered:

- **Expanding the Dataset:** Incorporating a more diverse and larger dataset with images from different sources will enhance the model's generalizability and performance.

- **Improving Model Architecture:** Exploring advanced deep learning models such as Vision Transformers (ViTs) or hybrid CNN-RNN architectures can potentially improve classification accuracy.

- **Multi-Class Classification:** Extending the system to classify pneumonia cases into bacterial and viral types will provide more clinically useful insights.

- **Reducing False Positives/Negatives:** Implementing techniques like ensemble learning or attention mechanisms can help refine the decision-making process and reduce errors.

- **Integration with Electronic Health Records (EHRs):** Connecting the model with hospital systems can streamline the diagnostic process and aid in automated report generation.

- **Mobile and Edge Deployment:** Optimizing the model for lightweight deployment on mobile devices or edge computing platforms will make it more accessible in low-resource settings.

- **Clinical Validation and Real-World Testing:** Collaborating with healthcare institutions to test the model in real-world scenarios and refine it based on clinical feedback.

- **Heatmap Visualization Enhancements:** Improving explainability by refining Grad-CAM heatmap visualizations to highlight pneumonia-affected regions more accurately.

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