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# Pneumonia Detection Using Chest Radiographs

**Apurva Nagare**
Department of Computer Engineering, SITRC Sandip Foundation, Nashik, India
E-mail: 1aapurvaavhad@gmail.com

**Ankita karale**
HOD, Department of Computer Engineering, SITRC Sandip Foundation, Nashik, India
E-mail: 2ankita.karale@sitrc.org

**Naresh Thoutam**
Department of Computer Engineering, SITRC Sandip Foundation, Nashik, India
E-mail: 3naresh.thoutam@sitrc.org

**Abstract**
Pneumonia is a serious respiratory infection that affects millions of people worldwide each year. It is caused by a range of pathogens—including bacteria, viruses, and fungi—and leads to lung inflammation and impaired breathing. Early and accurate diagnosis is essential for effective treatment, as timely intervention can significantly lower both morbidity and mortality rates.
In this study, we utilize advanced deep learning models to detect pneumonia from chest X-ray images, a widely used diagnostic tool in clinical practice. We implemented several state-of-the-art architectures, including Convolutional Neural Networks (CNN), InceptionResNetV2, Xception, VGG16, ResNet50, and EfficientNetV2L. These models were selected for their demonstrated performance in image classification tasks, particularly within the domain of medical imaging.
**Keywords:** Employing X-ray, images presents, affordable, non-intrusive, approach, scrutinizing, lung conditions.

**1. INTRODUCTION** The methodology of this study involved several key stages, beginning with the collection and preprocessing of a comprehensive chest X-ray dataset comprising both pneumonia cases and healthy controls. Preprocessing steps included image normalization, augmentation, and resizing to ensure uniformity and enhance model robustness. The dataset was then partitioned into training, validation, and test sets to facilitate effective model evaluation.
Following training on the preprocessed data, the performance of each deep learning model was assessed using standard evaluation metrics: accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC-ROC). Among the tested models, EfficientNetV2L delivered the highest performance, achieving an accuracy of 94.02%, highlighting its strong capability to detect pneumonia cases while minimizing false positives.
These findings underscore the potential of deep learning to enhance the diagnostic accuracy of pneumonia detection. By leveraging advanced models, healthcare providers can benefit from rapid and reliable screening methods, which support timely clinical decisions. Beyond improving diagnosis, our study also emphasizes the value of integrating artificial intelligence into routine

medical workflows to assist radiologists and clinicians.

Pneumonia is an infectious disease characterized by inflammation of the air sacs in one or both lungs and is commonly caused by bacteria, viruses, or fungi. Despite significant progress in medical imaging and diagnostic technology, pneumonia continues to be a leading cause of death globally. Traditional diagnostic approaches, such as manual interpretation of chest X-rays, can be labor-intensive and susceptible to human error. The rise of deep learning has introduced automated diagnostic systems capable of enhancing both the accuracy and efficiency of pneumonia detection. Deep learning models—particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)—have demonstrated effectiveness in interpreting medical imaging data, including chest X-rays and computed tomography (CT) scans. These models are adept at recognizing complex patterns within large datasets, enabling precise identification of abnormal lung conditions associated with pneumonia.

Ongoing advancements in deep learning continue to improve diagnostic methodologies, contributing to the development of more sophisticated and dependable tools in respiratory medicine. The burden of pneumonia is especially severe in low-resource and developing regions, where limited access to medical facilities, dense populations, pollution, and poor sanitation exacerbate the risk. In such settings, early detection and access to affordable care are critical to reducing mortality.

Radiographic assessment remains a fundamental aspect of evaluating respiratory illnesses. Imaging techniques such as X-rays, CT scans, and MRI are commonly employed to visualize lung conditions. Among these, chest X-rays offer a cost-effective, non-invasive means of examining lung health and play a central role in pneumonia diagnosis.

## 2. RELATED WORKS

Pneumonia is a widespread respiratory infection characterized by inflammation of the lungs, commonly caused by pathogens such as bacteria, viruses, or fungi. Early and accurate diagnosis is vital for effective treatment and disease management. In recent years, deep learning has emerged as a promising approach for automating pneumonia detection using chest X-ray images. By leveraging Convolutional Neural Networks (CNNs) trained on diverse and annotated datasets, these models can learn complex features and visual patterns indicative of pneumonia, such as infiltrates, white patches, abscesses, or pleural effusions.

The integration of deep learning into diagnostic workflows enhances accuracy, reduces human error, and increases overall healthcare efficiency. Continuous research and the availability of high-quality, labeled datasets are further refining the performance and reliability of these models.

While chest X-rays alone may not always be sufficient for a definitive pneumonia diagnosis, this research focuses on developing algorithms capable of detecting thoracic diseases using chest radiographs. Various pre-existing CNN architectures were evaluated, combined with traditional machine learning classifiers like Decision Trees (DT), Linear Discriminant Analysis (LDA), and Linear Regression for feature selection and classification. These models effectively extracted and refined features from the image datasets, achieving promising results and demonstrating improved performance with hybrid approaches.

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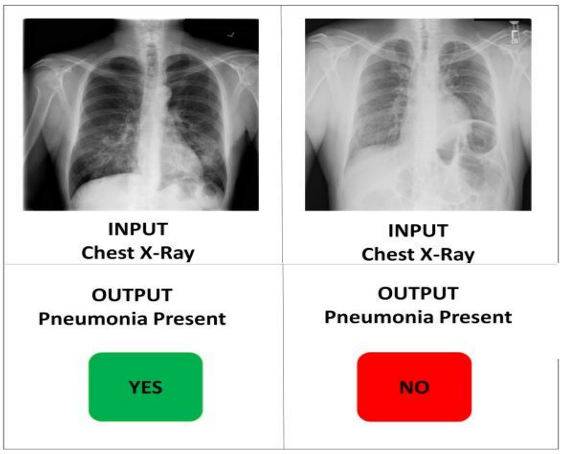
A notable contribution of the study was the implementation of DenseNet-121, a deep learning model comprising 121 convolutional layers. DenseNet showed superior diagnostic capabilities, achieving a higher F1 score compared to human experts. To address the issue of class imbalance, a Weighted Binary Cross-Entropy loss function was introduced—unlike standard binary loss, this approach assigns varying weights based on the class distribution, improving model sensitivity toward minority classes.

In addition to DenseNet, transfer learning models such as AlexNet and GoogLeNet were also employed for chest X-ray classification. The dataset was split into 68% for training, 17.1% for validation, and 14.9% for testing. Data augmentation and preprocessing techniques were applied to improve robustness and generalization. The models achieved remarkable results, with one setup reporting an AUC of 0.99, precision of 100%, and recall of 97.33%. An Attention-Guided CNN (AG-CNN) developed by Guan further enhanced these outcomes.

A proposed CNN architecture was also explored, designed to automatically classify X-ray images by progressively extracting features from stacked convolutional layers. As the depth of the CNN increases, it captures more intricate and abstract patterns, allowing better discrimination between pneumonia and non-pneumonia cases. The backpropagation algorithm was used to update model weights effectively during training.

Pneumonia remains a leading cause of death among children globally, particularly in South Asia and Sub-Saharan Africa. In 2016, there were approximately 1.2 million reported cases among children under five, resulting in 880,000 deaths. Even in developed nations such as the United States, pneumonia ranks among the top 10 causes of mortality. Timely detection and treatment are crucial in reducing pneumonia-related deaths, especially in high-prevalence regions.

This paper presents the design and evaluation of multiple CNN models for pneumonia detection from chest X-ray images. Six models were examined: two were custom CNNs with two and three convolutional layers, while the other four were pre-trained networks—VGG16, VGG19, ResNet50, and Inception-v3. The first and second models achieved validation accuracies of 85.26% and 92.31%, respectively. The accuracies for the pre-trained models were 87.28% (VGG16), 88.46% (VGG19), 77.56% (ResNet50), and 70.99% (Inception-v3), demonstrating varying performance based on architecture depth and complexity.



**Chest screening procedures**, commonly used to detect lung nodules, are also valuable for diagnosing other thoracic conditions such as **pneumonia**, **pleural effusion**, and **cardiomegaly**. Among these, pneumonia stands out as a serious infectious disease that affects millions worldwide, particularly individuals over the age of 65 and those with underlying chronic conditions such as asthma or diabetes [11].

**Chest X-rays** remain one of the most effective diagnostic tools for identifying pneumonia, as they help determine the extent and location of infection within the lungs. However, interpreting chest radiographs poses significant challenges for radiologists. The visual presentation of pneumonia on X-ray images can often be subtle or ambiguous and may closely resemble other conditions. Disorders such as **congestive heart failure** or **pulmonary fibrosis** can produce similar radiographic patterns, making accurate diagnosis through X-rays alone a complex and error-prone task..

## 3. MODULES AND DESCRIPTION

### 3.1 Data Input (11pt bold)

The system starts by ingesting chest X-ray images of patients, which serve as the raw data for the model.

### 3.2 Data Preprocessing

The input images undergo preprocessing, which includes steps like normalization, resizing, and noise reduction to enhance image quality.

### 3.3 Data Augmentation

To make the model more robust and avoid overfitting, the system applies various data augmentation techniques such as rotations, flips, and shifts.

### 3.4 Model Selection

Different deep learning models like CNN are selected based on the problem requirements.

### 3.5 Model Training

The selected models are trained on the preprocessed and augmented data. The training involves adjusting the model parameters to minimize prediction errors.

### 3.6 Model Evaluation

The trained models are evaluated using metrics like accuracy, precision, recall, and F1 score to determine their performance

### 3.7 Output Results:

Finally, the system outputs the diagnosis results, indicating whether the patient has pneumonia or not, based on the input X-ray images.

## 4. Proposed System

The **proposed system** is designed to develop a robust and fully automated approach for detecting **pneumonia** from chest radiographs (X-ray images). It utilizes advanced **Convolutional Neural Networks (CNNs)** to analyze medical images and accurately classify them into two categories: *pneumonia* and *normal*.

The model is trained on a large, labeled dataset of chest X-rays and applies deep learning techniques to automatically extract and learn subtle features associated with pneumonia. To enhance image quality and model generalization, several **preprocessing techniques**—

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including image augmentation and normalization—are employed. Additionally, **hyperparameter tuning** and **optimization strategies** are implemented to further improve the system's accuracy and efficiency.

To mitigate the challenges posed by **class imbalance**, commonly encountered in medical imaging datasets, the system incorporates **weighted loss functions**. The model's performance is evaluated using key metrics such as **accuracy**, **precision**, **recall**, and **F1-score**, ensuring a comprehensive assessment of its diagnostic capability.

This **automated pneumonia detection system** offers valuable assistance to radiologists by enabling faster and more accurate diagnoses. By reducing the reliance on manual interpretation, it contributes to improved clinical decision-making and better patient outcomes.

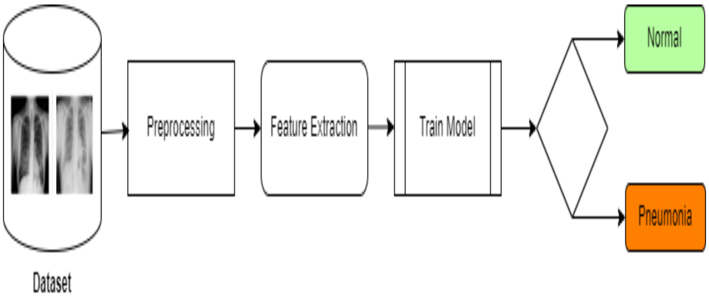


Fig 4. Architecture

We will be using **Chest X-ray images** for detecting **Pneumonia** in this deep learning project. You can download the dataset from the provided link: **Chest X-ray for Pneumonia Detection**. The dataset is already divided into three folders: train, test, and val.

- The train folder contains images that will be used to train the model.
- The test folder contains images to evaluate the model's performance after training.
- The val (validation) folder is used to fine-tune and optimize the model's hyperparameters.

Each folder contains two categories of images: Normal and Pneumonia, which will be used to classify and detect the presence of pneumonia in chest X-ray images.

The diagram appears to represent a simple user interface or dashboard for a healthcare monitoring system that might be part of an IoT-based patient care system.

## 5. LITERATURE SURVEY

A Novel Transfer Learning-Based Approach for Pneumonia Detection in Chest X-ray Images

Pneumonia remains one of the leading causes of death globally and can be triggered by viral, bacterial, or fungal infections. Despite the widespread use of chest X-rays for diagnosis, accurately identifying pneumonia through radiographs is a challenging task, even for seasoned medical professionals. This study introduces a novel deep learning framework utilizing transfer learning to streamline pneumonia detection for both experts and novices.

In this approach, features are extracted from chest X-ray images using various neural network models pre-trained on the ImageNet dataset. These features are then input into a classifier for prediction. The researchers developed five distinct models and evaluated their individual performances. Ultimately, they proposed an ensemble model that combines the outputs of all

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pre-trained networks. This ensemble approach outperformed each individual model and achieved state-of-the-art performance, recording 96.4% accuracy and 99.62% recall on unseen data from the Guangzhou Women and Children's Medical Center dataset.

In conclusion, the ensemble model offers a highly effective and accurate solution for pneumonia detection. Its integration into clinical workflows could enhance diagnostic precision and assist healthcare professionals in making quicker, more informed decisions. Future research may explore the integration of additional medical data and assess the model's effectiveness across diverse healthcare environments to ensure its robustness and generalizability.

Pneumonia Classification Using Deep Learning from Chest X-ray Images During COVID-19

The outbreak of COVID-19 in late 2019 triggered a global health emergency, officially declared a pandemic by the World Health Organization (WHO) on March 11, 2020. Although RT-PCR remains the standard for COVID-19 detection, it faces limitations such as high cost, low sensitivity, and reliance on skilled personnel. In contrast, chest X-ray (CXR) images offer a faster, more accessible alternative for initial screening.

This study proposes a deep learning-based approach using the pre-trained AlexNet model to classify CXR images into multiple categories: COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia, and normal. The model supports binary, three-way, and four-way classifications.

**Key results include:**

COVID-19 vs. Normal: 99.16% accuracy, 97.44% sensitivity, 100% specificity

Bacterial Pneumonia vs. Normal: 91.43% accuracy, 91.94% sensitivity, 100% specificity

Non-COVID Viral Pneumonia vs. Normal: 94.43% accuracy, 98.19% sensitivity, 95.78% specificity

COVID-19 vs. Non-COVID Viral Pneumonia: 99.62% accuracy, 90.63% sensitivity, 99.89% specificity

Three-Way Classification: 94.00% accuracy

Four-Way Classification: 93.42% accuracy

These findings demonstrate the model's robustness in classifying various respiratory conditions, offering a promising tool for efficient and accurate COVID-19 screening alongside other types of pneumonia.

## 6. EXPERIMENTAL ANALYSIS

The performance of deep learning models depends on their ability to process and interpret data accurately to make predictions. To evaluate this performance, several metrics are used, including accuracy, precision, recall, and the F1 score. Accuracy measures the overall correctness of the model's predictions. Precision indicates the proportion of true positive cases out of all predicted positives, focusing on the accuracy of positive predictions. Recall, on the other hand, highlights the model's ability to identify all actual positive cases, reducing false negatives. Together, these metrics provide a well-rounded evaluation of the model's effectiveness in data processing and prediction.

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### 6.1 Data Set Chest X-ray Images

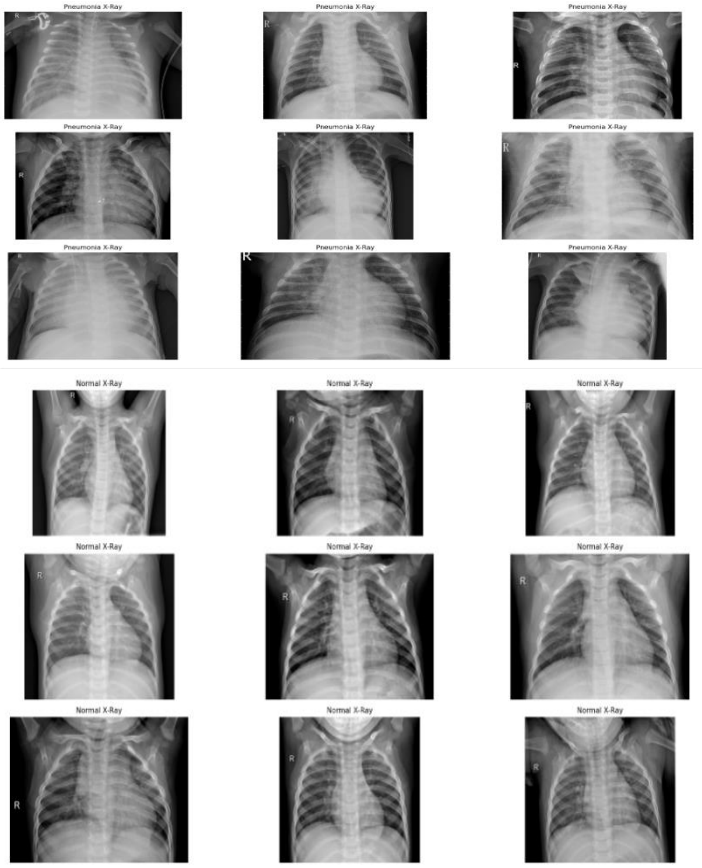


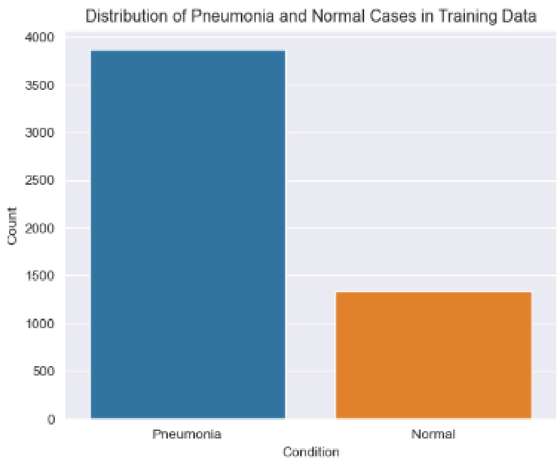
**Figure 6.1 Data Set Chest X-ray**

- Shows X-ray images categorized as **Pneumonia and Normal**.
- Used for **training visualization and data augmentation**.

### 6.2 Distributions of Pneumonia and Normal

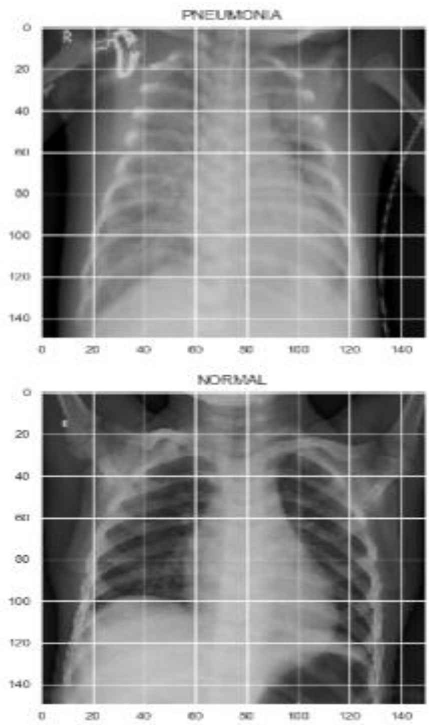
Since Pneumonia cases dominate the dataset, the model learns to classify most images as Pneumonia.

This can result in poor performance on Normal cases.



### 6.3 Distributions of Pneumonia and Normal

### 6.3 Feature Grid Visualization




### 6.3 Feature Grid Visualization

- Shows grid overlays on Pneumonia and Normal X-ray images.
- Likely used for feature extraction visualization.

### 6.4 Model Summary

- Describes a CNN architecture with layers:
- Conv2D & MaxPooling2D: Extract features
- BatchNormalization: Stabilizes learning.
- Dropout: Prevents overfitting.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 150, 150, 32) | 320 |
| batch_normalization (BatchNormalization) | (None, 150, 150, 32) | 128 |
| max_pooling2d (MaxPooling2D) | (None, 75, 75, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 75, 75, 64) | 18,496 |
| dropout (Dropout) | (None, 75, 75, 64) | 0 |
| batch_normalization_1 (BatchNormalization) | (None, 75, 75, 64) | 256 |
| max_pooling2d_1 (MaxPooling2D) | (None, 38, 38, 64) | 0 |
| conv2d_2 (Conv2D) | (None, 38, 38, 64) | 36,928 |
| batch_normalization_2 (BatchNormalization) | (None, 38, 38, 64) | 256 |
| max_pooling2d_2 (MaxPooling2D) | (None, 19, 19, 64) | 0 |
| conv2d_3 (Conv2D) | (None, 19, 19, 128) | 73,856 |
| dropout_1 (Dropout) | (None, 19, 19, 128) | 0 |
| batch_normalization_3 (BatchNormalization) | (None, 19, 19, 128) | 512 |
| max_pooling2d_3 (MaxPooling2D) | (None, 10, 10, 128) | 0 |
| conv2d_4 (Conv2D) | (None, 10, 10, 256) | 295,168 |
| dropout_2 (Dropout) | (None, 10, 10, 256) | 0 |
| batch_normalization_4 (BatchNormalization) | (None, 10, 10, 256) | 1,024 |
| max_pooling2d_4 (MaxPooling2D) | (None, 5, 5, 256) | 0 |
| flatten (Flatten) | (None, 6400) | 0 |
| dense (Dense) | (None, 128) | 819,328 |
| dropout_3 (Dropout) | (None, 128) | 0 |
| dense_1 (Dense) | (None, 1) | 129 |

**Figure 6.4 Model Summary**

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### 6.5 Training Log

- Shows epochs and training progress.
- accuracy: Training accuracy improves over epochs.
- loss: Decreasing loss means the model is learning.
- val_accuracy: Validation accuracy fluctuates, which suggests possible overfitting.
- ReduceLROnPlateau: Learning rate is reduced when progress stagnates

```
163/163 ━━━━━━━━━━━━━━━━━━━━ 222s 1s/step - accuracy: 0.8122 - loss: 1.3019 - val_accuracy: 0.5000 - val_loss: 49.9127 - learning_rate: 0.0010
Epoch 2/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 181s 1s/step - accuracy: 0.8871 - loss: 0.3045 - val_accuracy: 0.5000 - val_loss: 47.3616 - learning_rate: 0.0010
Epoch 3/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 0.9186 - loss: 0.2131
Epoch 3: ReduceLROnPlateau reducing learning rate to 0.0003000000142492354.
163/163 ━━━━━━━━━━━━━━━━━━━━ 171s 1s/step - accuracy: 0.9186 - loss: 0.2132 - val_accuracy: 0.5000 - val_loss: 25.6300 - learning_rate: 0.0010
Epoch 4/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 186s 1s/step - accuracy: 0.9338 - loss: 0.1821 - val_accuracy: 0.5000 - val_loss: 31.8639 - learning_rate: 3.0000e-04
Epoch 5/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 0.9470 - loss: 0.1369
Epoch 5: ReduceLROnPlateau reducing learning rate to 9.000000427477062e-05.
163/163 ━━━━━━━━━━━━━━━━━━━━ 196s 1s/step - accuracy: 0.9470 - loss: 0.1369 - val_accuracy: 0.5000 - val_loss: 21.8913 - learning_rate: 3.0000e-04
Epoch 6/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 192s 1s/step - accuracy: 0.9656 - loss: 0.1031 - val_accuracy: 0.6250 - val_loss: 0.8514 - learning_rate: 9.0000e-05
Epoch 7/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 198s 1s/step - accuracy: 0.9657 - loss: 0.1021 - val_accuracy: 0.6250 - val_loss: 2.5826 - learning_rate: 9.0000e-05
Epoch 8/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 196s 1s/step - accuracy: 0.9603 - loss: 0.1148 - val_accuracy: 0.6875 - val_loss: 0.4743 - learning_rate: 9.0000e-05
Epoch 9/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 176s 1s/step - accuracy: 0.9626 - loss: 0.1078 - val_accuracy: 0.7500 - val_loss: 0.5275 - learning_rate: 9.0000e-05
Epoch 10/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 208s 1s/step - accuracy: 0.9623 - loss: 0.1044 - val_accuracy: 0.6875 - val_loss: 1.0955 - learning_rate: 9.0000e-05
Epoch 11/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 0s 1s/step - accuracy: 0.9716 - loss: 0.0929
Epoch 11: ReduceLROnPlateau reducing learning rate to 2.700000040931627e-05.
163/163 ━━━━━━━━━━━━━━━━━━━━ 209s 1s/step - accuracy: 0.9716 - loss: 0.0929 - val_accuracy: 0.6250 - val_loss: 0.8338 - learning_rate: 9.0000e-05
Epoch 12/12
163/163 ━━━━━━━━━━━━━━━━━━━━ 216s 1s/step - accuracy: 0.9656 - loss: 0.1022 - val_accuracy: 0.6250 - val_loss: 1.0284 - learning_rate: 2.7000e-05
```

**Figure 6.5 Training Log**

### 6.6 Training & Validation Accuracy and Loss

- Left Plot:
  - Training Accuracy (green): Increases steadily, which is expected.
  - Validation Accuracy (red): Peaks at some point but then declines, indicating overfitting.
- Right Plot:
  - Training Loss (green): Remains low.
  - Validation Loss (red): Starts high and fluctuates, indicating the model struggles with generalization.

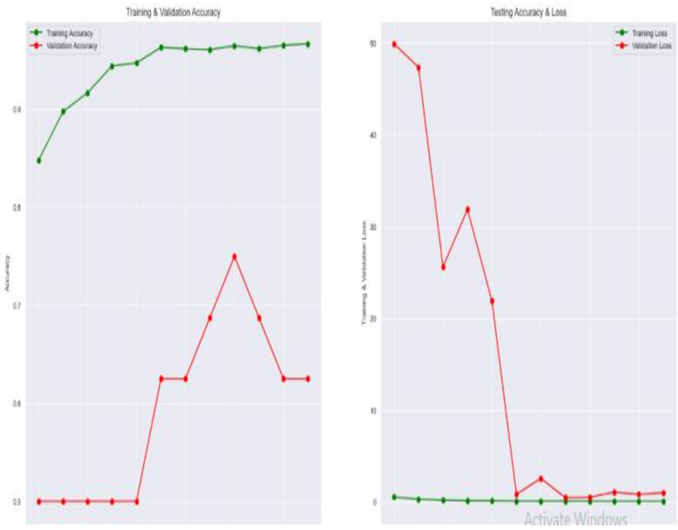


**Figure 6.6 Accuracy and Loss**

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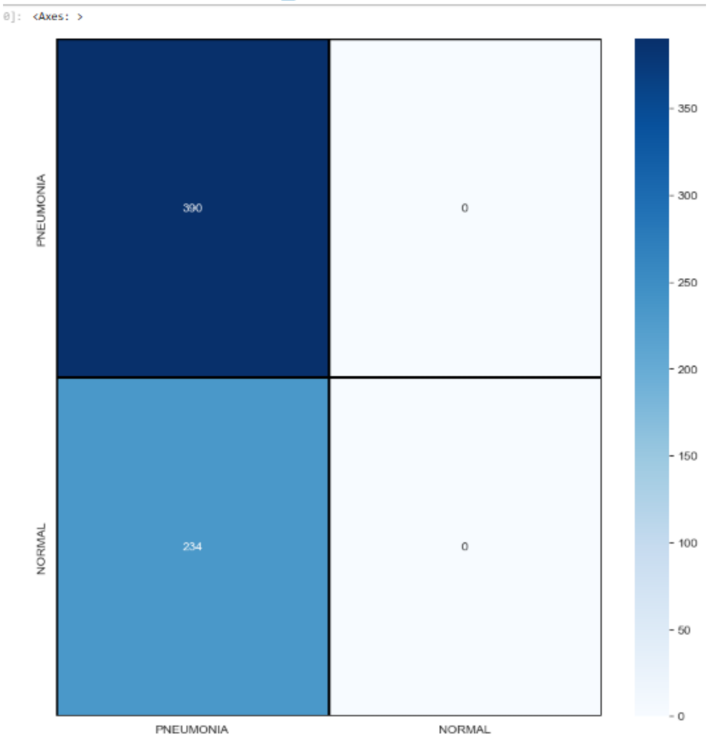
**6.7 Confusion Matrix.**




**6.7 Confusion Matrix**

- Indicates model performance.
- Model predicts **only one class (PNEUMONIA)** and fails to classify NORMAL cases.
- 390 Pneumonia cases correctly classified, but **234 Normal cases misclassified as Pneumonia**.
- Model is **highly biased toward one class.**

**6.8 Prediction Results**

- Shows images with **Predicted Class vs. Actual Class**.
- The model incorrectly classifies all NORMAL and some PNEUMONIA images as class 0 (Pneumonia).

Indicates the model has poor **generalization**

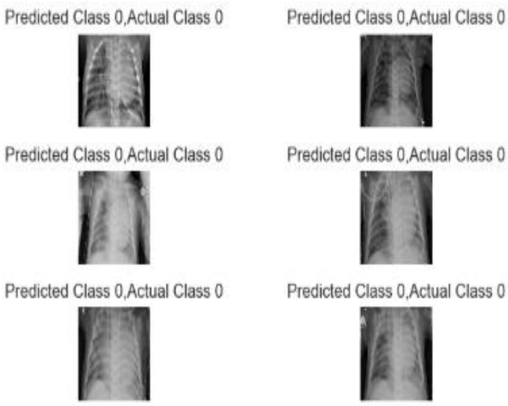



**Figure 6.8 Prediction Results**

**EVALUATION PARAMETERS**

The evaluation of pneumonia detection models using deep learning with chest X-ray images involves assessing various metrics, including accuracy, recall, precision, and the F1 score. Accuracy measures the model's ability to correctly predict both positive and negative cases, while specificity focuses on how well the model identifies negative cases accurately. Precision reflects the proportion of correctly classified positive cases out of all predicted positives. The F1 score provides a balanced measure by combining both precision and recall, offering healthcare professionals a comprehensive tool to make informed decisions and ultimately improve patient care.

## 6. CONCLUSION

In conclusion, this research proposed the classification of digital chest X-ray images for pneumonia detection using deep learning techniques. Several CNN models were implemented, including InceptionResNetV2, Xception, VGG16, ResNet50, and EfficientNetV2L, using Python and Google Colab. The initial experiments yielded promising results, with accuracy rates of 88.78%, 88.94%, 90.7%, 91.66%, 87.98%, and 94.02%, respectively. These accuracy values demonstrate the potential of these models to serve as decision support tools for pneumonia diagnosis based on X-ray images.

However, the study acknowledges certain limitations and the need for further research. One challenge is the risk of overfitting due to the limited dataset size. To mitigate this, the authors recommend collecting more data to improve the model's generalization capability.

Additionally, the paper stresses the importance of exploring various preprocessing techniques and CNN configurations to enhance performance. Data augmentation techniques are also proposed to expand the dataset, which can help improve generalization. Moreover, the authors suggest incorporating additional X-ray datasets that include labels for various pathologies to further refine and strengthen the models' diagnostic capabilities.

## APPENDIX

Appendixes, if needed, appear before the acknowledgement.

## ACKNOWLEDGEMENT

The heading of this section must not be numbered. You may wish to thank those who have supported you and your work.

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