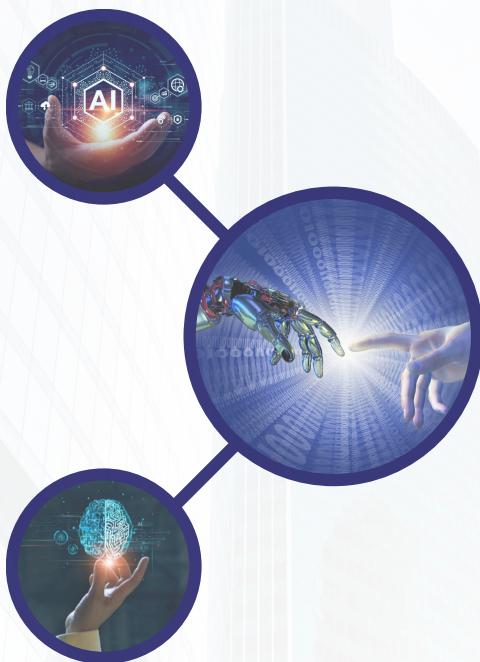


# Convolutional Neural Networks

## for Detection and Segmentation of Pneumonia in Medical Images



# PROJECT REPORT

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# Detection and Segmentation of Pneumonia in Medical Images Using Convolutional Neural Networks

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**Abstract:** This project explores the use of Convolutional Neural Networks (CNN) for the detection of pneumonia in chest X-ray images. The dataset used comprises labelled images categorized as either "NORMAL" or "PNEUMONIA," with a total of 1,341 normal and 3,875 pneumonia images in the training set. Various pre-processing techniques such as image resizing, normalization, and data augmentation (shear, zoom, horizontal flips) were employed to enhance model performance and address the challenge of class imbalance. The CNN architecture consists of multiple convolutional blocks, followed by fully connected layers for feature extraction and classification. The model achieved an accuracy of 92.31%, with a recall of 98.21%, indicating its strong ability to correctly identify pneumonia cases.

**Keywords:** Pneumonia detection, Convolutional Neural Networks (CNN), Data augmentation, Chest X-ray classification, Model performance

## I. INTRODUCTION

Medical image classification is a vital component of disease diagnosis, particularly in healthcare. It involves the automatic analysis of medical images to categorize them into specific classes, such as normal or pneumonia. Traditionally, this process required medical practitioners to manually extract features from images, a time-consuming and error-prone task. The classification process consists of two main steps: first, extracting key features from the images (such as shapes, textures, or edges) and then using these features to build models that can classify the images. In the past, early image classification methods relied on raw pixel data, which posed challenges due to variations in how objects appeared in different images (e.g., *different backgrounds, angles, or poses*). However, with advancements in artificial intelligence and deep learning, particularly Convolutional Neural Networks (CNNs), the need for manual feature extraction has been eliminated. These models can automatically learn and extract relevant features from raw images, improving both the accuracy and efficiency of the classification process. As a result, AI-driven medical image classification has revolutionized the way diseases are diagnosed, making the process faster, more accurate, and accessible for healthcare professionals.

## II. LITERATURE REVIEW

Recent advancements in deep learning have significantly enhanced the accuracy of pneumonia detection using medical imaging. Various convolutional neural network (CNN) architectures, such as VGG-16, VGG-19, ResNet50, and Inception-V3, have been deployed with transfer learning to classify pneumonia from X-ray images. Jain et al. achieved 71–88% accuracy, while Dey et al. obtained up to 98% accuracy using VGG-19 combined with classifiers like SVM and random forest. More specialised models, like VGG-16 with GradCAM, DenseNet-201, and CovXNet [13], further improved classification performance, with accuracies reaching 96.7% and beyond, depending on the dataset and model configurations.

Hybrid architectures and ensemble learning methods also played a critical role in improving detection performance. Jin et al. proposed a hybrid model that achieved 98.62% accuracy, while Rajaraman et al. utilized ensemble learning with CNNs, yielding accuracy rates between 94% and 99%. Additionally, large-scale datasets, such as the RSNA Pneumonia Detection Challenge, enabled the development of highly robust models like VGG, which achieved 94.62% accuracy. These advancements, along with innovations in interpretability like ProtoPNet, showcase the evolving landscape of deep learning in

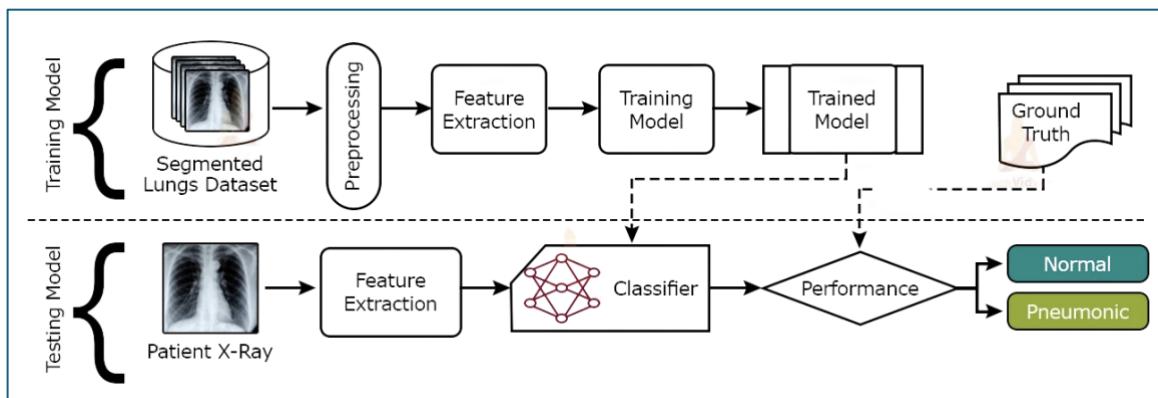
medical image classification, offering significant promise for enhancing diagnostic accuracy in pneumonia detection.

### III. OVERVIEW OF THE SYSTEM

#### 1. Existing vs Proposed System

**Traditionally**, pneumonia detection relies on chest X-rays, blood or sputum cultures, and a Complete Blood Count (*CBC*) to diagnose and identify the causative pathogens. *Chest X-rays* are the most common imaging technique used to visualize lung abnormalities such as consolidations or infiltrates indicative of pneumonia. *Blood or sputum cultures* help confirm the presence of infection, while a *CBC* provides information on the body's immune response. Advanced lab tests are often required in more complex cases. Despite their effectiveness, these traditional methods are time-consuming and can be prone to human error, especially when interpreting chest X-rays, which may lead to delays in diagnosis and treatment.

The **proposed** system aims to enhance pneumonia detection with deep learning, particularly *Convolutional Neural Networks (CNNs)*, to automatically analyze chest X-ray images. By training the model on a large dataset of labelled images, the system can learn to identify key features indicative of pneumonia, such as specific patterns and textures. This approach allows for rapid, accurate, and consistent diagnoses, eliminating human error and reducing interobserver variability. Additionally, it can assist healthcare professionals in areas with limited access to radiologists, enabling quicker decision-making and improving patient outcomes through more timely intervention.



*Figure 1: Working Methodologies*

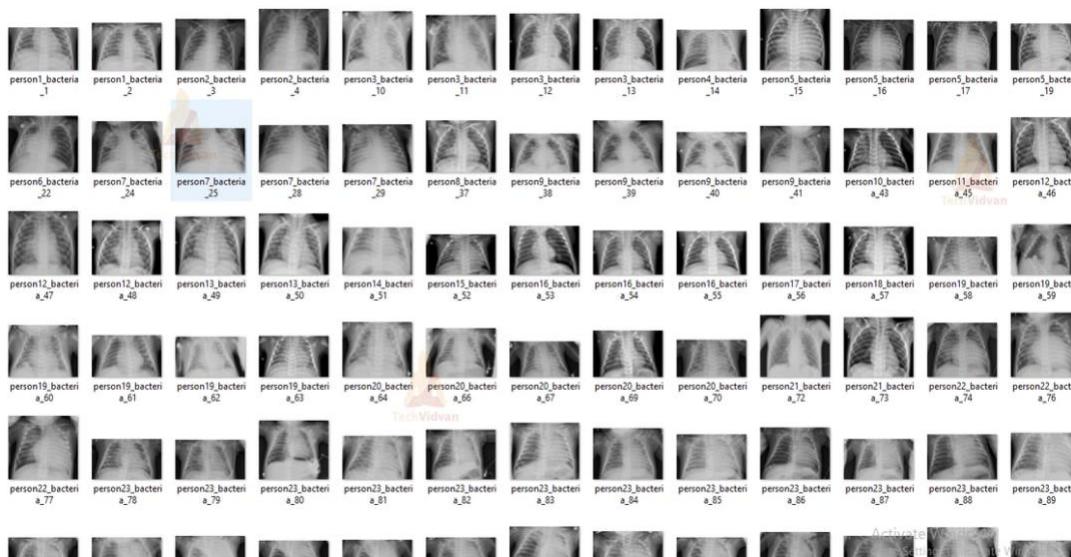
In this Project, we will detect Pneumonia using Deep Learning. We will create a model that will classify whether the patient is normal or suffering from pneumonia by looking at Chest X-ray images. The algorithm or the model that we will create should be extremely accurate because the lives of people are at stake.

### IV. DATASET

The dataset used in this study is the **Kaggle Chest X-Ray Images Dataset**, which is publicly available and widely utilized for pneumonia detection research. It has been pre-split into three subsets: training, validation, and test data, ensuring a structured approach for training and evaluating the deep learning model. The dataset contains labelled chest X-ray images classified into two categories: **NORMAL** and **PNEUMONIA**. These images represent various instances of chest X-rays that were taken from patients, with the **NORMAL** category indicating images without any signs of

pneumonia and the **PNEUMONIA** category containing images that show characteristics typical of pneumonia, such as lung infiltrates or consolidation.

- **Training Data:** The training dataset consists of 1,341 NORMAL images and 3,875 PNEUMONIA images. This data is used to train the deep learning model, enabling it to learn to distinguish between the two categories based on features present in the X-ray images.
- **Validation Data:** For validation, the dataset includes 8 NORMAL and 8 PNEUMONIA images. This small validation set is used to fine-tune the model's hyperparameters and monitor its performance during the training phase to prevent overfitting.
- **Test Data:** The test dataset contains 234 NORMAL and 390 PNEUMONIA images, which are used to evaluate the final performance of the trained model. The model's accuracy, precision, recall, and other metrics are calculated using this test data to assess its generalization ability and its effectiveness in real-world scenarios.

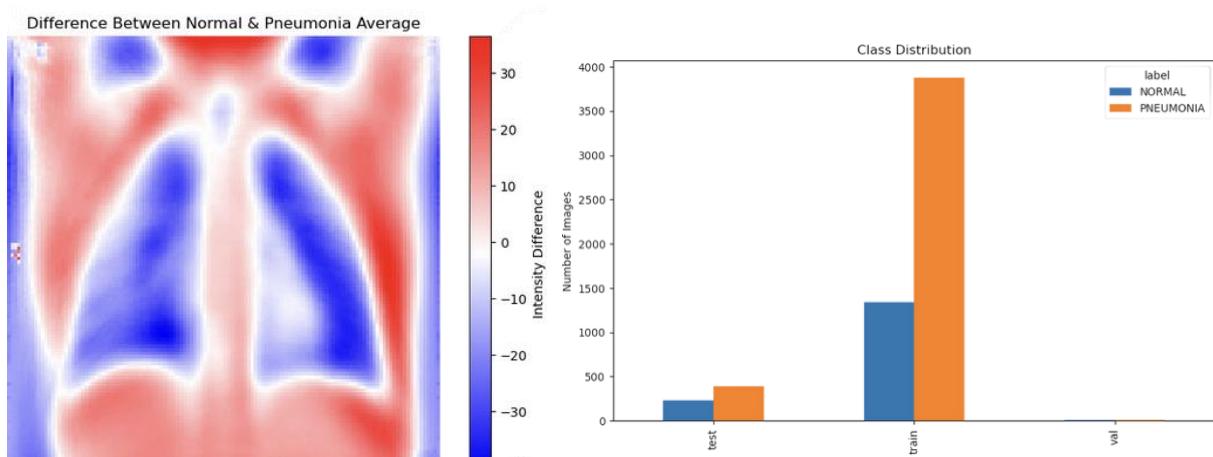


**Figure 2: Dataset Sample**

## V. METHODOLOGY

### Step 1: Exploratory Data Analysis (EDA)

It is the initial step in the data analysis process, aimed at understanding the dataset's underlying structure, detecting anomalies, and summarizing key characteristics. EDA often involves the use of visualization techniques and statistical tools to uncover patterns, relationships, and trends within data.



**Figure 4.3: General EDA**

The **heatmap** shows intensity differences between NORMAL and PNEUMONIA chest X-rays: white indicates no difference, red highlights pneumonia features (e.g., lung opacity), and blue emphasizes normal lung structures.

## Step 2: Data Preprocessing

Data preprocessing is a crucial phase in the analysis pipeline, as it significantly influences the accuracy and reliability of the results. Without proper preprocessing, raw datasets may yield erroneous outcomes and compromise the quality of insights. To ensure robust analysis, the dataset was carefully preprocessed before applying any data mining techniques. The preprocessing steps included:

- **Resizing:** All images were resized to ***150x150 pixels*** to ensure uniform input dimensions, simplifying preprocessing and allowing the model to process all data consistently.
- **Normalization:** The pixel values were scaled to the range [0, 1] by dividing the original pixel values (ranging from 0-255) by 255. This step stabilizes training and improves convergence by standardizing the input data.
- **Data Augmentation:** To artificially increase the diversity of the training dataset, ***data augmentation*** techniques such as random shear, zoom, and horizontal flips were applied. This helps the model generalize better and become more robust to variations in input data.
- Keras's ***ImageDataGenerator*** was utilized to dynamically handle the tasks of resizing, normalization, and augmentation during the training process, ensuring smooth and efficient data preprocessing.
- **Class Imbalance Handling:** To address the class imbalance between **NORMAL** and **PNEUMONIA** categories, ***class weights*** were applied. Higher weights were assigned to the minority class (NORMAL) and to the majority class (PNEUMONIA) to ensure that the model didn't favour the more prevalent class.

## Step 3: Model Building

### Input Layer

The input layer defines the shape of the input data, which consists of images resized to ***150x150 pixels*** with 3 colour channels (RGB). This ensures that the images can be efficiently processed by the neural network, maintaining consistency in the input dimensions across all images.

### Convolutional Blocks

**Block 1:** Low-Level Features This block is responsible for detecting simple, low-level features such as edges and textures in the image. It consists of two Conv2D layers with 16 filters. These layers convolve the input image to detect patterns like edges, followed by a MaxPool2D layer, which performs down-sampling and reduces the spatial dimensions of the feature maps, helping to focus on the most important features.

**Block 2:** Intermediate Features The second block detects more complex features by utilizing two SeparableConv2D layers with 32 filters. These layers use *depthwise* separable convolutions, which are computationally efficient and can capture more detailed features. A *BatchNormalization* layer follows to stabilize training by normalizing the activations, reducing the internal covariate shift. Another MaxPool2D layer further downsamples the output.

**Block 3:** Higher-Level Features This block continues to extract increasingly complex and abstract features from the image. The architecture includes another set of SeparableConv2D layers with larger filter sizes to capture finer details and patterns.

**Block 4:** Advanced Features with Regularization This block focuses on extracting the most abstract features and includes two SeparableConv2D layers with 128 filters. To prevent overfitting, Dropout with a rate of 0.2 is introduced. This randomly drops a portion of the neurons during training, which helps regularize the model and improves its generalization. The *BatchNormalization* and *MaxPool2D* layers are again used for stabilization and down-sampling.

### Fully Connected Layers

After extracting features through the convolutional layers, the fully connected layers combine all the high-level features learned by the network. These layers are heavily regularized to prevent overfitting and ensure that the model does not memorize the training data but instead generalizes well to unseen data.

### Output Layer

The output layer uses a Sigmoid activation function, which is suitable for binary classification tasks. It outputs a probability between [0, 1], indicating the likelihood of the image being classified as PNEUMONIA or NORMAL. If the output is closer to 1, the model predicts pneumonia, while an output closer to 0 indicates the image is classified as normal.

### Convolutional Operations

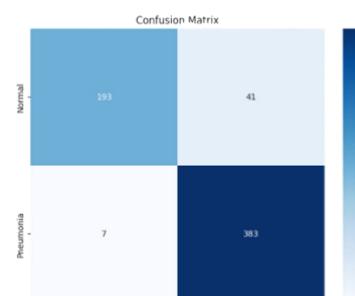
- **Conv2D** layers are essential for detecting features like edges, shapes, and abnormalities in chest X-ray images, such as lung boundaries or signs of infection and inflammation.
- **MaxPooling** layers help focus on the most prominent features in the image, progressively reducing the spatial dimensions of the feature maps while retaining important information, such as signs of pneumonia or healthy lung structures.

## V. RESULTS

The provided image presents key evaluation metrics for a model designed to detect pneumonia based on X-ray images. Here's the explanation of each component:

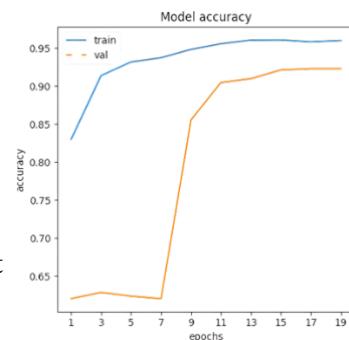
### 1. Confusion Matrix

- **True Positives (383):** The number of pneumonia cases correctly classified as pneumonia.
- **True Negatives (193):** The number of normal cases correctly classified as normal.
- **False Positives (41):** The number of normal cases incorrectly classified as pneumonia (Type I Error).
- **False Negatives (7):** The number of pneumonia cases incorrectly classified as normal (Type II Error).



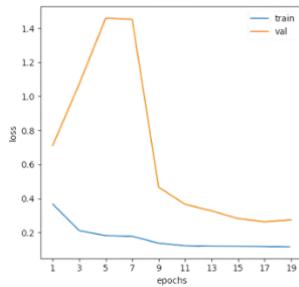
### 2. Model Accuracy

- Shows how well the model performed during training and validation over 20 epochs.
- **Training Accuracy** (Blue line) consistently increases and stabilizes at approximately 95%.
- **Validation Accuracy** (Orange line) starts lower but significantly improves and stabilizes around 90%.



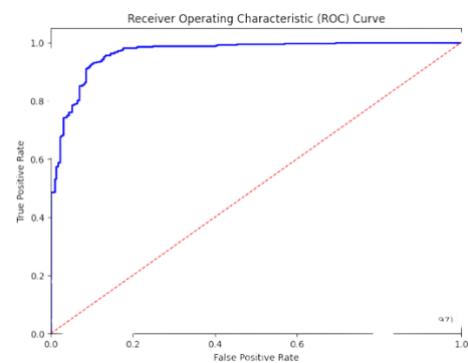
### 3. Model Loss

- The graph depicts the loss function over training epochs.
- **Training Loss** (Blue line) decreases steadily, indicating that the model is learning effectively.
- **Validation Loss** (Orange line) initially spikes, possibly due to overfitting in early epochs but eventually stabilizes.



### 4. ROC Curve

- This graph plots the **True Positive Rate (TPR)** against the **False Positive Rate (FPR)**.
- A steep curve near the top-left corner indicates the model's good ability to discriminate between pneumonia and normal cases.
- **AUC (Area Under the Curve)** likely approaches 1, which indicates the model performs well in classifying both classes, with high sensitivity and low false positive rates.



In summary, the model shows good performance in classifying pneumonia and normal cases, with high accuracy and a favourable ROC curve. The confusion matrix indicates minimal misclassifications.

## VI. CONCLUSION, RECOMMENDATION & FUTURE WORK

The model achieved **92.31% accuracy**, demonstrating its ability to correctly classify most of the chest X-ray images as either **NORMAL** or **PNEUMONIA**. The **precision** of **90.33%** indicates that the model is proficient in identifying pneumonia cases while minimising false positives, ensuring that only a small number of normal cases are incorrectly labeled as pneumonia. With a **recall (sensitivity)** of **98.21%**, the model excels at detecting pneumonia, successfully identifying nearly all true positive cases, which is crucial in medical diagnosis. The **F1-score** of **0.94** strikes a balance between precision and recall, providing an overall measure of the model's effectiveness. These results highlight the model's strong performance in detecting pneumonia, making it a promising tool for medical image analysis.

Challenges such as imbalanced data, small dataset size, privacy concerns, and computational constraints were mitigated through various techniques, including data augmentation, dropout, and early stopping. These strategies not only helped in overcoming issues like overfitting but also improved the model's generalization and training efficiency. Despite these efforts, the project still faces challenges such as high computational requirements and long training times.

Looking ahead, future improvements can be made by expanding the dataset for more diversity and better generalization. Incorporating advanced architectures like **ResNet** or **EfficientNet** could further enhance performance. Additionally, integrating the model into real-world applications like hospital radiology systems or mobile apps would make it more practical for clinical use. Implementing model interpretability techniques like **Grad-CAM** or saliency maps could help visualize and explain the model's decision-making process, increasing trust in its clinical deployment.

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