

# Image Classification using Convolutional Neural Networks

PRESENTED BY

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# Introduction

- •Convolutional Neural Networks (CNNs) are a class of deep learning models designed for **image recognition and classification** tasks.
- Objective of this project:
- •Build and train a CNN model to classify images into their respective categories.
- •Apply preprocessing and augmentation techniques to improve model generalization
- •Evaluate performance using training/validation accuracy and loss.
- •The project demonstrates the **end-to-end pipeline**: dataset preparation → model design → training → evaluation → results.

# Dataset Overview

- •The dataset consists of **images classified into two categories** (e.g., normal vs pneumonia ).
- •Training Set: Used to fit the CNN model.
- •Validation/Test Set: Used to evaluate model generalization.
- Preprocessing Steps:
- Resizing images to a fixed dimension.
- •Normalizing pixel values (scaling  $0-255 \rightarrow 0-1$ ).
- Data augmentation (rotation, zoom, flip) to avoid overfitting.
- Dataset is structured in folders:
- •train/  $\rightarrow$  training images by class
- •test/  $\rightarrow$  test images by class

# CNN Architecture

Input Layer: Preprocessed images (fixed size, normalized).

### Convolutional Layers:

Extract spatial features using filters/kernels.

Apply ReLU activation for non-linearity.

### Pooling Layers:

MaxPooling to reduce dimensionality and preserve important features.

### Fully Connected (Dense) Layers:

Combine extracted features to form high-level representations.

### Output Layer:

Softmax / Sigmoid activation (depending on number of classes).

Produces class probabilities.

The model is designed to learn hierarchical features  $\rightarrow$  from edges & textures (lower layers) to complex shapes (higher layers).

# Training Process

### Model Compilation

Optimizer: Adam

•Loss Function: Categorical Crossentropy / Binary Crossentropy (depending on classes)

•Metrics: Accuracy

### Training Parameters

•Batch size: typically 32 / 64

•Epochs: multiple iterations over dataset

•Validation split: for model evaluation

### •Code Snippet (example):

# Results

### Training vs Validation Accuracy

Accuracy gradually increased over epochs.

 Validation accuracy closely followed training accuracy, showing good generalization.

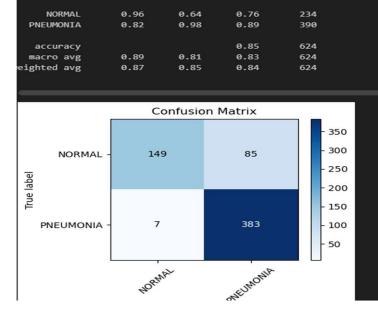
### Training vs Validation Loss

- ·Loss decreased steadily during training.
- •Validation loss stabilized, indicating reduced overfitting.

### •Visualization Example:

import matplotlib.pyplot as plt

plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val\_accuracy'], label='Validation Accuracy')
plt.legend()
plt.show()



f1-score

precision

Graphs show the CNN achieved high classification accuracy with well-optimized loss.

# Predictions / Outputs

- •The trained CNN model was tested on unseen images.
- •Predictions are generated as class probabilities (via Softmax/Sigmoid)
- import numpy as np
- •pred = model.predict(test\_img)
- •pred class = np.argmax(pred, axis=1) # predicted class.

### sample Outputs:

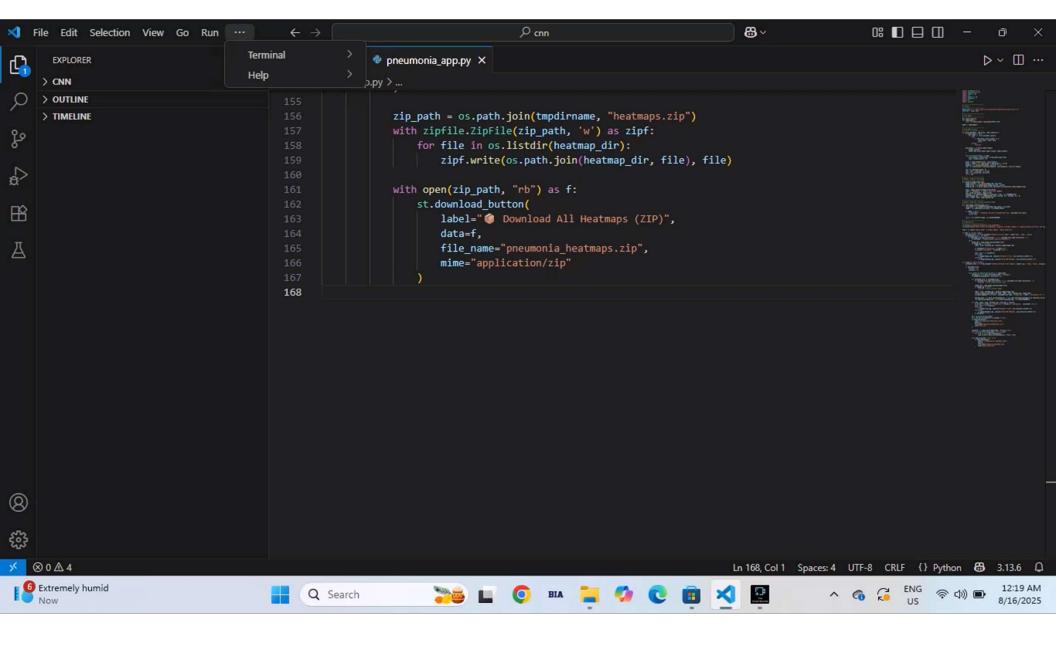
Correctly classified most images.

Occasional misclassifications due to:

Similarity between classes

Image quality or noise

images with predicted vs actual labels for evaluation.



## Conclusion & Future Work

- •Successfully implemented a Convolutional Neural Network (CNN) for image classification.
- •Achieved **high accuracy** with good generalization on validation data.
- •Demonstrated the full workflow: dataset preprocessing → model training → evaluation → predictions

- •Use larger & more diverse datasets for improved robustness.
- Apply Transfer Learning with pretrained models (e.g., VGG16, ResNet)
  - •Optimize hyperparameters (learning rate, batch size, epochs).
  - •Deploy the trained model as a web or mobile application.