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PRESENTATION SLIDE

PNEUMONIA IMAGES CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS

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PSM2 Presentation Video Playlist:
https://www.youtube.com/playlist?list=PLxxcvSZsRk_rNAkRMo3raBApsfBk4OAQk

Innovating Solutions

Chapter 1
Problem Background

Pneumonia accounted for 12.2% of death in Malaysia in 2020(Tong,2023), Pneumonia is a respiratory infection that is typically brought on by fungi, bacteria or viruses and is characterized by inflammation of the lung's air sacs. The severity of the symptoms varies depending on age and general health, including coughing, fever, chest pain, and difficulty breathing (Castelilio,2023). Because of this, people need to take precautions to detect it early to avoid severe health complications. Exams such as chest X-rays, physical examinations, and medical histories are all part of the diagnosis process to detect these deathly diseases. While the Conventional approaches to pneumonia detection certainly good but it still has it limitation and several drawbacks.

Problem Statement

Current pneumonia detection largely relies on radiological imaging modalities such as CT scans and X-rays, manually interpreted by skilled radiologists or physicians. This traditional method, however, is hampered by subjectivity, labor-intensiveness, and delays in diagnosis and treatment, particularly in resource-limited healthcare settings (Wong et al., 2018; Ramirez, 2023; Gamache, 2024). These challenges, including variability in interpretation and sensitivity to early or subtle signs of pneumonia, necessitate new approaches.

Research Goal

The goal of this research is to evaluate the performance of Convolutional Neural Networks (CNNs) to detect pneumonia images and classify them correctly whether the patient has Pneumonia or not.

Research Objectives

1. To study deep learning methods in classifying Pneumonia using data images
2.To develop the convolutional neural networks model in classifying Pneumonia using images
3.To evaluate the performance of convolutional neural networks in Pneumonia images classification using accuracy, recall and F1 measurement.

Research Scopes

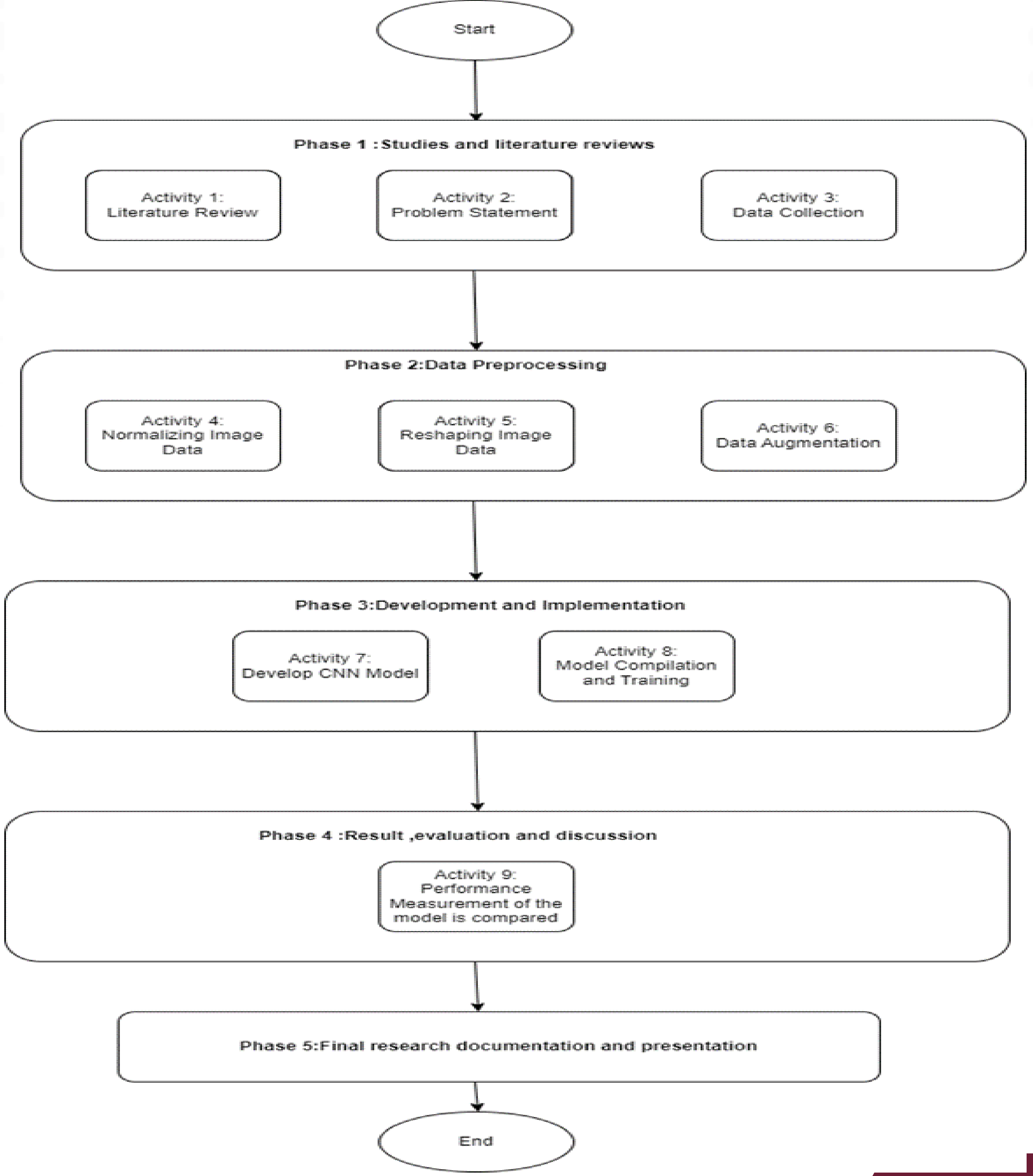
1)This research focuses on finding the outcomes of performance of CNN to detect pneumonia images.
2)We will used normal and pneumonia patient chest x-ray images as the dataset for this research from pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center.
3)We will use the computational method of convolutional neural networks (CNNs) to classify chest X ray images.
4)The platform that we will be Google Colab and VS Code to run our python coding for machine learning.

Chapter 2
Comparison from previous studies

Title	Reference	Dataset	Method	Measurements	Outcomes	Limitation
Multi-class classification of lung diseases using CNN models.	Hong, M., Rim, B., Lee, H., Jang, H., Oh, J., & Choi, S. (2021). Multi-class classification of lung diseases using CNN models. Applied Sciences, 11(19), 9289	https://cloud.google.com/healthcare/docs/resources/public-datasets/nih-chest The U.S. National Institutes of Health (NIH) Open Dataset comprises 10,000 PNG images of Normal, Pneumonia, and Pneumothorax	Convolutional Neural Network (CNN)	Accuracy, sensitivity, specificity, and inference time	When measured with the NIH dataset, the model achieves an accuracy of 85.32%, showcasing its effectiveness in accurately classifying lung diseases. Moreover, when evaluated with the four-class predictions using data from Soonchunhyang University Hospital in Cheonan, the model achieves an average accuracy of 96.1%, average sensitivity of 92.2%, average specificity of 97.4%, and an average inference time of 0.2 seconds.	If abnormal situation occurs, the model may not perform well
Comparative Study of Pneumonia Detection Using Supervised Learning (Feed Forward Back Propagation) and Unsupervised Learning (Radial Basis Function).	.Latta, A., Avhad, S., Mahajan, D., & Shintre, R. (2021). Comparative Study of Pneumonia Detection Using Supervised Learning (Feed Forward Back Propagation) and Unsupervised Learning (Radial Basis Function). International Research Journal of Engineering and Technology	https://www.kaggle.com/code/paultimothymooney/detecting-pneumonia-in-x-ray-images The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (Pneumonia/Normal). There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).	Artificial Neural Networks(ANN)	Accuracy	Achieving exceptional training and testing accuracy exceeding 96%.	ANNs are prone to overfitting, wherein the model learns to memorize the training data's noise and specific patterns instead of capturing the underlying relationships. Overfitted models may perform well on the training data but generalize poorly to new data, leading to decreased performance in pneumonia detection when applied to unseen patient cases.

Deep Learning Approaches for Detecting Pneumonia in COVID-19 Patients by Analyzing Chest X-Ray Images	Hasan, M. K., Ahmed, S., Abdullah, Z. E., Monirujjaman Khan, M., Anand, D., Singh, A., ... & Masud, M. (2021). Deep learning approaches for detecting pneumonia in COVID-19 patients by analyzing chest X-ray images. Mathematical Problems in Engineering, 2021, 1-8.	The data used to support the findings of this study are freely available at https://www.kaggle.com/prashant268/chest-xray-covid19-pneumonia.	Convolutional Neural Network (CNN)	accuracy, recall, sensitivity, specificity, and precision.	The model predicted pneumonia with an average accuracy of 91.69%, sensitivity of 95.92%, and specificity of 91%.	Prone to error when handling complex network structures.
Viral and Bacterial Pneumonia Detection Using Artificial Intelligence in the Era of COVID-19	Ozsoz, M., Ibrahim, A. U., Serte, S., Al-Turjman, F., & Yakoi, P. S. (2020). Viral and bacterial pneumonia detection using artificial intelligence in the era of COVID-19.	We obtained COVID-19 pneumonia, non-COVID-19 viral pneumonia, bacterial pneumonia, and normal CXR images from the following website: •153 images from GitHub (https://github.com/ieee8023/covid-chestxray-dataset) •We obtained CXR images made available by Kermany et al., 2018 [42].	Transfer Learning	Accuracy, sensitivity,specificity	For 3 classes (COVID-19, bacterial pneumonia, and healthy) testing accuracy of 93.42%, sensitivity of 89.18%, and specificity of 98.92% for 4 classes (COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia, and healthy).	Used all datasets of COVID-19 pneumonia. This challenge makes it difficult to generalize our results.

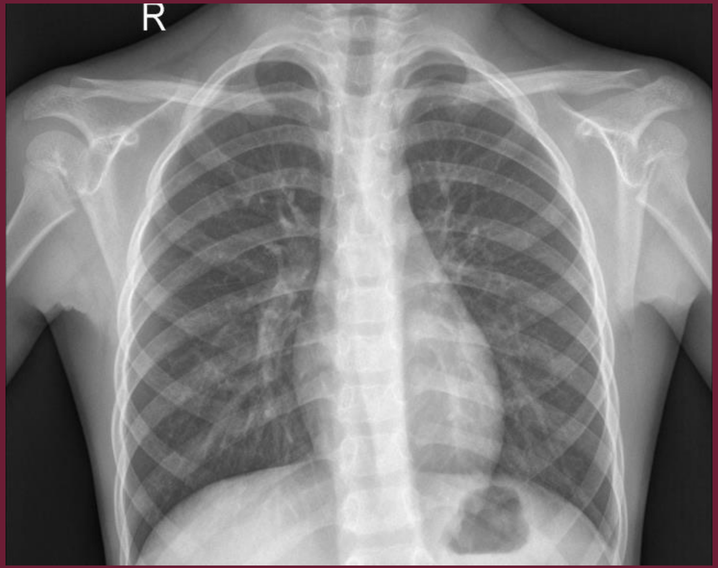
Chapter 3
Flowchart Diagram



Performance measurement

Performance Evaluation	Formula
Accuracy	Total Number of Predictions / Number of Correct Predictions
Precision	True Positives / (False Positives + True Positive)
Recall	True Positives / (False Negatives + True Positives)
F1-Score	2 × ((Precision +Recall) / (Precision× Recall))

Data Overview



CHEST X-RAY IMAGES OF NORMAL PATIENT

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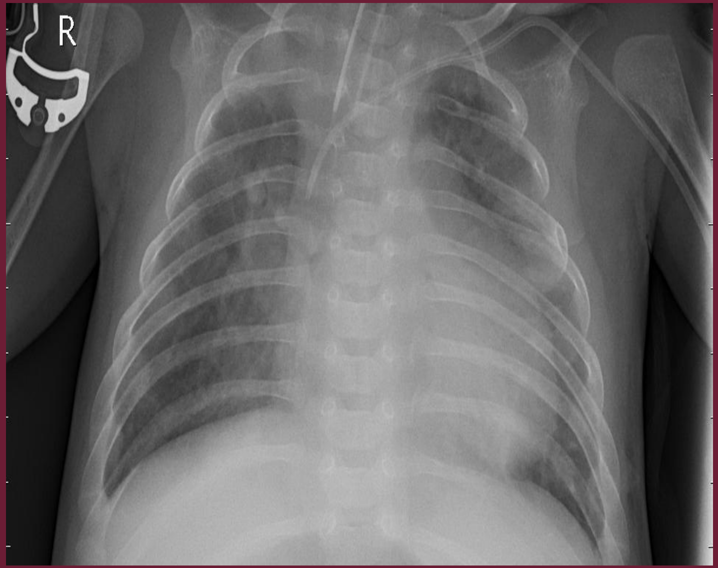


CHEST X-RAY IMAGES OF PNEUNOMIA PATIENT

- Source: Kaggle (Guangzhou Women & Children’s Medical Center)
- Original size: 5,863 images
- **Used: ~586 images (10%) only**

Chapter 4
Data Preprocessing

1.Dataset Organized

- The dataset is organized into 3 folders (train, test,val) and contains subfolders for each image category (Pneumonia/Normal)

2.Labels and Image Size

Labels and image size are specified:

•Defines the categories 'PNEUMONIA' and 'NORMAL'.

3.Loading Data

•Reading Images: Images are read from directories based on labels.

•Dividing pixel values by 255,helps the model train more efficiently

•Grayscale Conversion: Images are converted to grayscale to simplify the data.

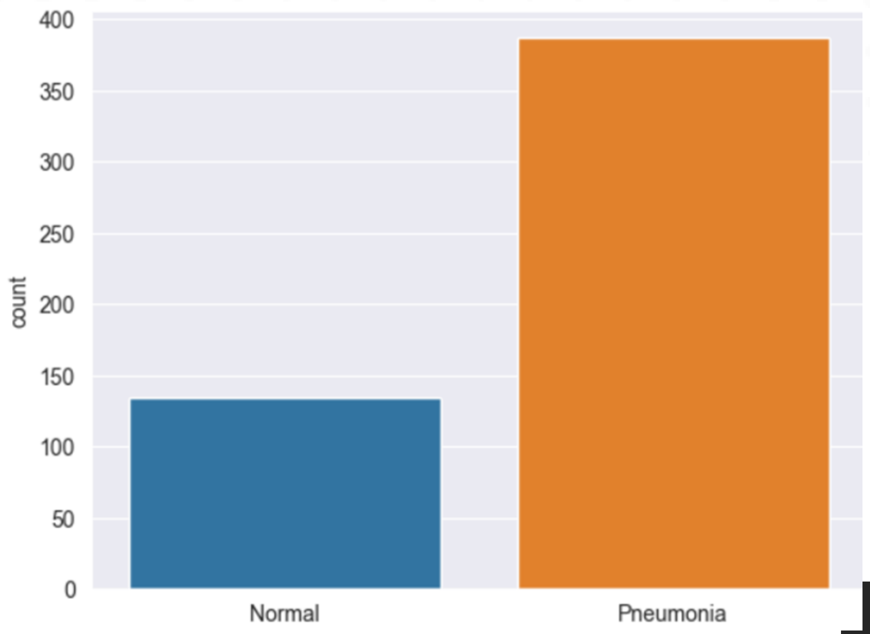
•Resizing: Images are resized to 150x150 pixels for uniformity.

•Normalization: Pixel values are scaled to the range [0, 1].

•Reshaping: Images are reshaped to the format (number of images, 150, 150, 1) to fit the CNN input requirements.

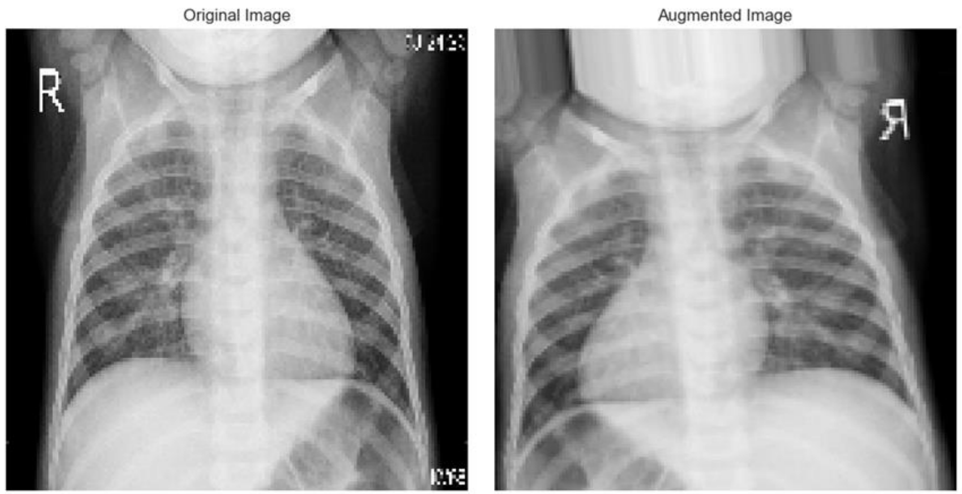
•Labeling: Each image is labeled according to its directory ('PNEUMONIA' or 'NORMAL').

4. The distribution of classes in the training data is visualized to check for balance .As shown on the image , The data seems imbalanced . To increase the no. of training examples, we will use data augmentation.



Data Augmentation

1. Randomly rotate some training images by 30 degrees
2. Randomly Zoom by 20% some training images
3. Randomly shift images horizontally by 10% of the width
4. Randomly shift images vertically by 10% of the height
5. Randomly flip images horizontally.



Building the CNN Model

- Model Architecture: The CNN consists of multiple convolutional layers, batch normalization, max-pooling layers, dropout for regularization, and dense layers. The output layer uses a sigmoid activation function for binary classification.
- Model Compilation: The model is compiled with the ‘Adam' optimizer and 'binary_crossentropy' loss function.
- Callbacks: EarlyStopping, ReduceLROnPlateau

- **Input:** 150 × 150 grayscale image
- **Conv2D:** 32 filters, 3×3 kernel, ReLU, same padding
- **BatchNormalization**
- **MaxPooling2D:** 2×2, same padding
- **Dropout:** 0.4
- **Conv2D:** 64 filters, 3×3 kernel, ReLU, same padding, L2 regularization
- **BatchNormalization**
- **MaxPooling2D:** 2×2, same padding
- **Dropout:** 0.5
- **Conv2D:** 128 filters, 3×3 kernel, ReLU, same padding, L2 regularization
- **BatchNormalization**
- **MaxPooling2D:** 2×2, same padding
- **Dropout:** 0.5
- **Flatten**
- **Dense:** 128 units, ReLU, L2 regularization
- **Dropout:** 0.6
- **Dense (Output):** 1 unit, Sigmoid activation
- **Optimizer:** Adam (learning rate = 0.00005)
- **Loss:** Binary Crossentropy

Model Performance

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Result with different epochs but constant learning rate is 0.00001

Epochs	Training Accuracy	Evaluation Accuracy	Result
12(Research Paper)	0.83	0.63	Overfitting
30	0.92	0.80	Overfitting
70	0.94	0.74	Overfitting
100	0.92	0.81	Overfitting
120	0.93	0.85	Good Fit
150	0.93	0.88	Good Fit
170	0.94	0.90	Good Fit
200(Best result)	0.94	0.93	Good Fit
220	0.93	0.88	Good Fit

Results with different learning rates and different epochs

Epochs	Learning Rate	Training Accuracy	Evaluation Accuracy	Result
12	0.01	0.86	0.63	Overfitting
30	0.001	0.89	0.79	Overfitting
70	0.0001	0.92	0.81	Good Fit
100	0.000001	0.92	0.89	Good fit

Chapter 5 Model Performance

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Results with different models for 10% of the dataset

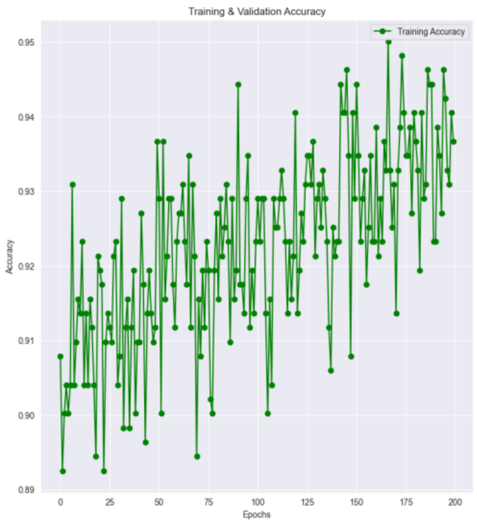
Models	Epochs	Learning Rate	Training Accuracy	Evaluation Accuracy	Result
EfficientNetB0	12	0.00001	0.74	0.63	Overfitting
DenseNet121	12	0.00001	0.91	0.90	Good fit
ResNet50	12	0.00001	0.85	0.87	Underfitting
InceptionV3	12	0.00001	0.89	0.82	Overfitting

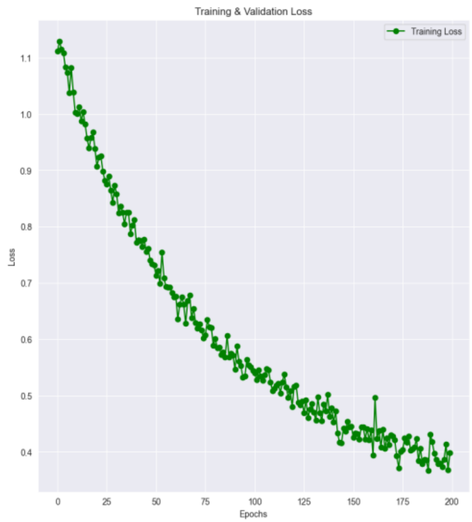
Results with different learning rates but constant epochs is 12.

Learning Rate	Training Accuracy	Evaluation Accuracy	Result
0.1	0.93	0.79	Overfitting
0.01	0.91	0.74	Overfitting
0.001	0.91	0.81	Overfitting
0.0001	0.89	0.74	Overfitting
0.000001	0.91	0.63	Severe Overfitting

Model Evaluation

Model performance

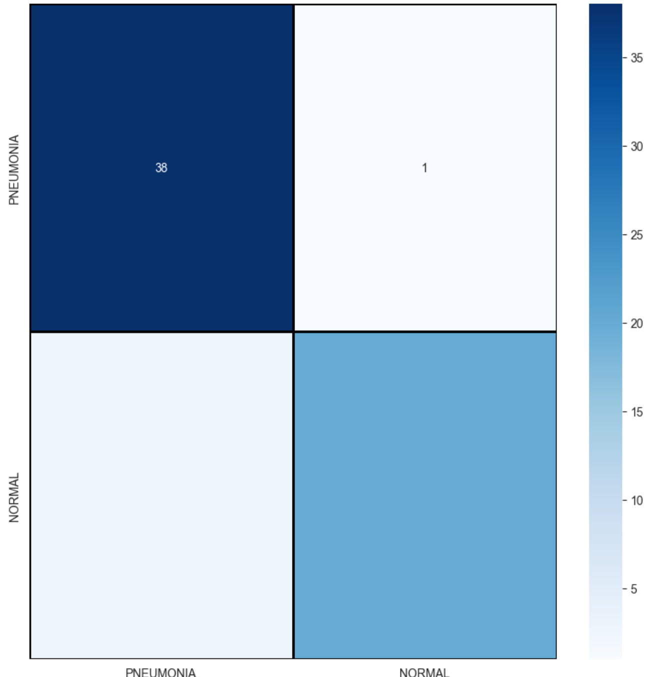




Classification Report

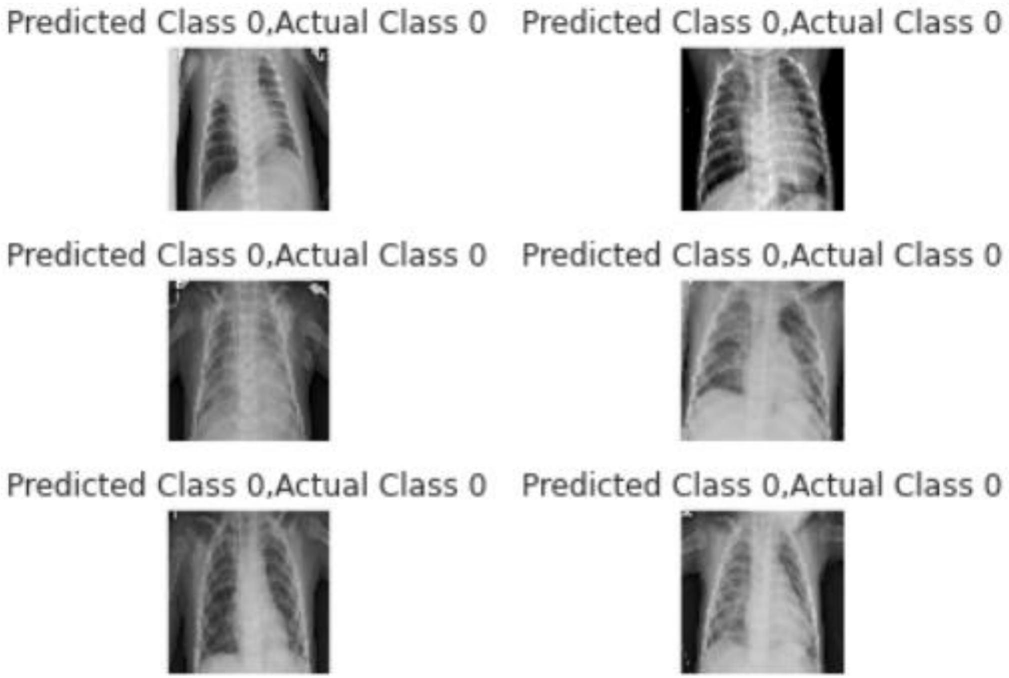
	precision	recall	f1-score	support
Pneumonia (Class 0)	0.93	0.97	0.95	39
Normal (Class 1)	0.95	0.87	0.91	23
accuracy			0.94	62
macro avg	0.94	0.92	0.93	62
weighted avg	0.94	0.94	0.93	62

Classification matrix

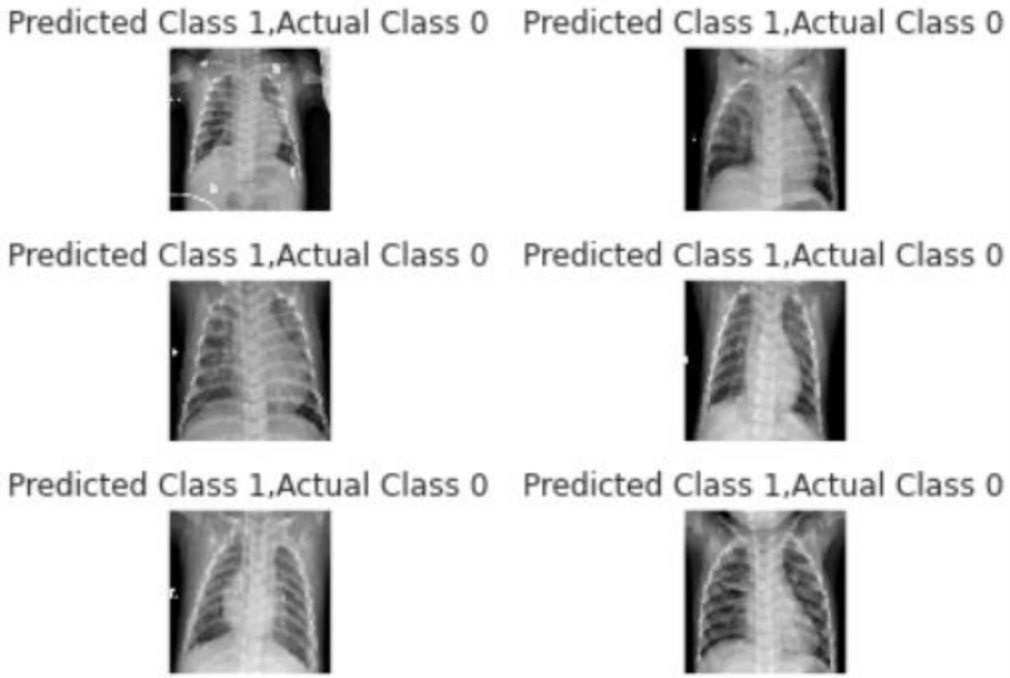


Visualizing Correct and Incorrect Predictions

Correct Prediction



Incorrect Prediction



Conclusion

The project faced several limitations, most notably the use of only 10% of the dataset, which led to overfitting and reduced the model's ability to generalize. Pretrained models like DenseNet121 and ResNet50 performed poorly under such limited data, while class imbalance and computational constraints further affected performance and training flexibility. For future work, expanding the dataset is essential to improve robustness and reduce bias, while exploring more advanced architectures and stronger regularization techniques may enhance accuracy and stability. Clinical validation, integration with radiologist feedback, and the use of interpretability tools such as Grad-CAM are also crucial next steps. Despite these challenges, the custom CNN model achieved strong results, demonstrating its potential as a lightweight, effective tool for pneumonia detection in chest X-ray images.

THANK YOU

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