COVID-19 Classification from Chest X-Ray Images

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Introduction

The COVID-19 pandemic created an urgent, global need for rapid and accessible diagnostic tools. To meet this demand, our project leverages the power of Artificial Intelligence to perform a differential diagnosis from chest X-ray images.
We have developed and trained a Convolutional Neural Network (CNN) that accurately distinguishes between the radiological markers of COVID-19, viral pneumonia, and healthy lungs. This provides a fast, automated, and scalable screening tool designed to support clinicians, supplement traditional testing, and improve diagnostic accessibility.

Methodology

Our methodology follows the structured pipeline illustrated in the flowchart. The process begins with Data Preparation, where our dataset of 6,432 chest X-rays is resized, normalized, and expanded using data augmentation.

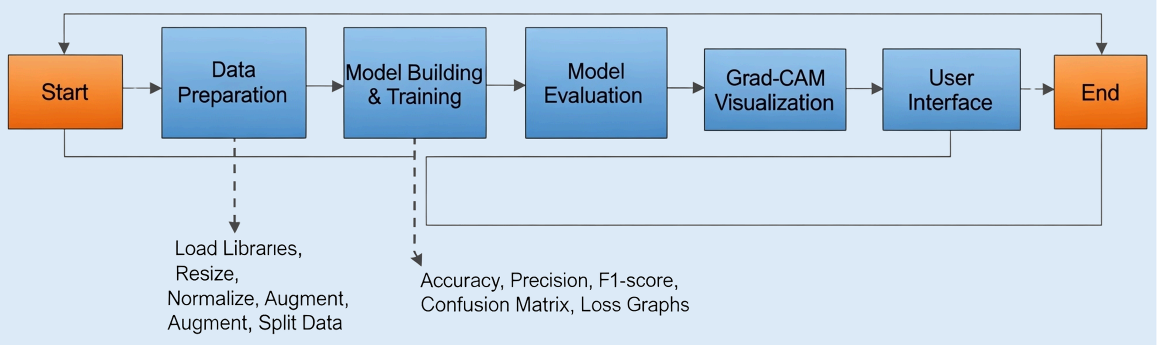


Figure 1: **Flowchart**

A Convolutional Neural Network (CNN) is then constructed and trained on this data. For evaluation, the data is split into dedicated training, validation, and test sets. While more rigorous methods like K-fold cross-validation exist, the exceptional performance our CNN achieved on the independent test set (AUC = 0.99) provided a strong and sufficient validation of its effectiveness. Finally, Grad-CAM is used to interpret the model's decision-making process before its integration into a final User Interface.

Model

This project uses a Convolutional Neural Network (CNN) for the automated detection of COVID-19 in chest X-rays.

- **Structure**: Built with 3 convolutional layers using ReLU activation to learn key non-linear patterns.
- **Input:** Processes images with a shape of (100, 100, 3).
- **Regularization:** Employs dropout and L2 regularization to prevent overfitting and improve model generalization.
- **Output:** A final SoftMax layer produces the probabilities for a multi-class classification (COVID-19, Pneumonia, Healthy).

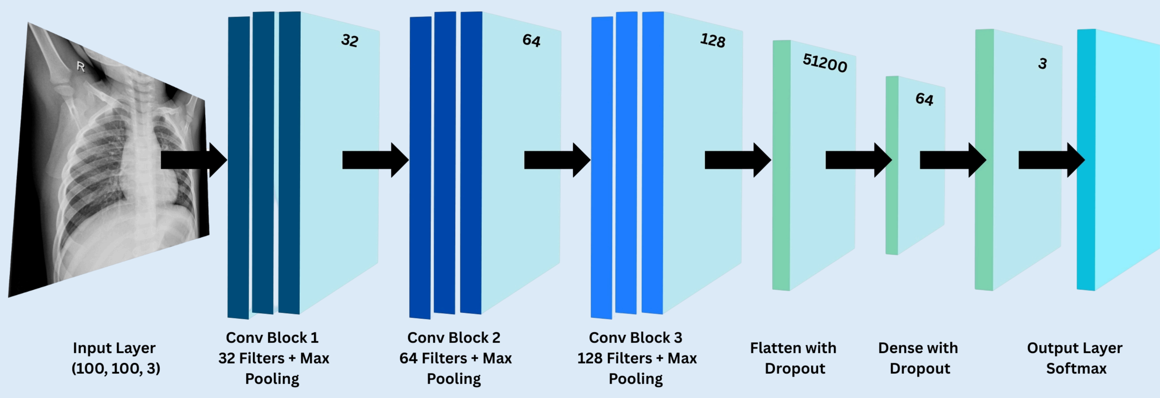


Figure 2: **CNN Model**

Key Findings:

- A 3-layer CNN architecture was found to be optimal for this diagnostic task.
- The model was trained on a dataset of 6,432 X-ray images, demonstrating the need for a sufficient data volume for accurate classification.
- Data augmentation techniques were critical for success. They significantly improved performance by both expanding the dataset and providing essential invariance to shifts and rotations in the images.
- The results confirm that this CNN-based approach is a very effective and scalable tool for mass testing scenarios during a pandemic.

Results

The model demonstrates high performance and robust generalization on the independent test set. The key evaluation metrics are presented below.

Classification Report: Validation Set

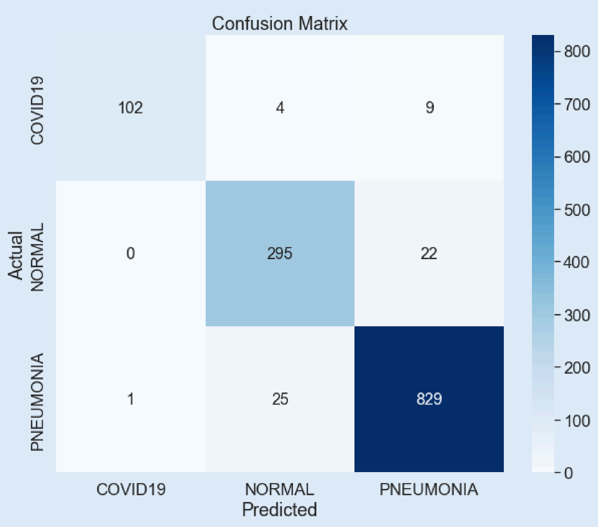
Metric	Precision	Recall	F1-Score	Support
COVID-19	1	0.92	0.95833	50
Normal	0.82836	0.91736	0.87059	121
Pneumonia	0.96418	0.93895	0.9514	344
Accuracy			0.93204	515
Macro Avg	0.93085	0.92544	0.92677	515
Weight Avg	0.93575	0.93204	0.93309	515

Classification Report: Test Set

Metric	Precision	Recall	F1-Score	Support
COVID19	0.99029	0.88696	0.93578	115
Normal	0.91049	0.9306	0.92044	317
Pneumonia	0.96395	0.96959	0.96676	855
Accuracy			0.9526	1287
Macro Avg	0.95491	0.92905	0.94099	1287
Weight Avg	0.95314	0.9526	0.95258	1287

Figure 3:
Confusion Matrix

This 3x3 matrix visualizes the model's performance, showing the counts of True Positives, True Negatives, False Positives, and False Negatives across all classes



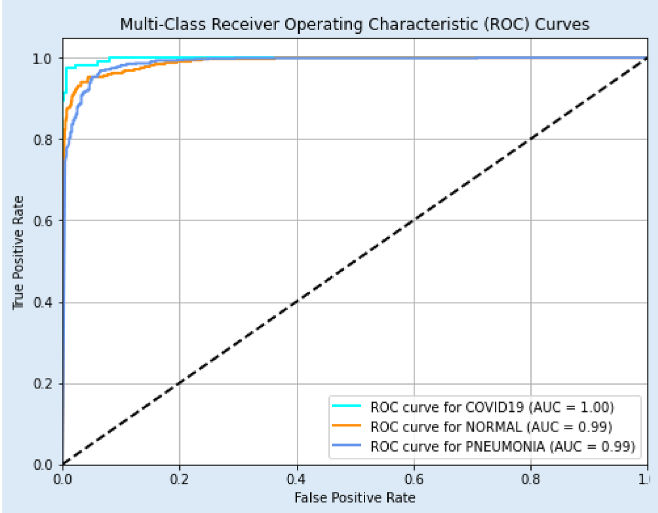
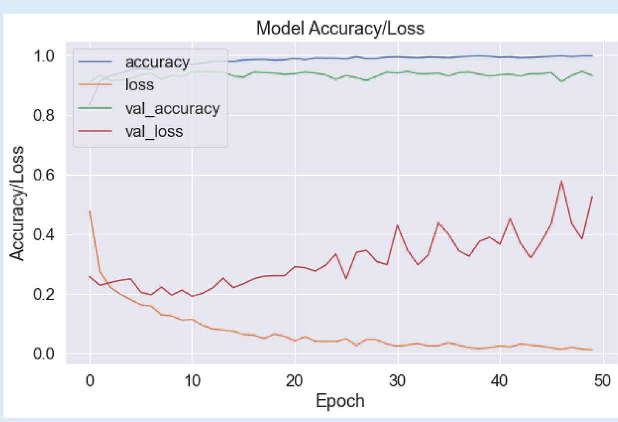


Figure 4:
Multi-Class ROC Curves

These curves illustrate our model's diagnostic ability across all classes, demonstrating excellent performance with AUC scores of 0.99 or higher.

Figure 5:
Model Accuracy/Loss

This plot illustrates the model's training progression over epochs, showing both accuracy and loss for the training and validation sets.



Discussion

Our deep learning model demonstrates robust diagnostic capabilities for accurately differentiating COVID-19, Normal, and Pneumonia cases from chest X-rays. Specifically, the classification report (Table, Figure 3) and confusion matrix (Figure 3) highlight high precision, recall, and F1-scores across all classes, indicating a low misdiagnosis rate for critical conditions crucial for timely clinical intervention. The multi-class ROC AUC curves (Figure 4), consistently near 1.0, further affirm the model's exceptional discriminative ability across these distinct pathologies. Furthermore, the accuracy and loss curves (Figure 5) illustrate stable training and strong generalization to the validation set, suggesting the model's stability and readiness for new, unseen data.

Visualization

To interpret our model's decisions, we utilized Gradient-weighted Class Activation Mapping (Grad-CAM). This technique generates heatmaps that highlight the specific regions within chest X-ray images most influential in our model's predictions. The original X-ray images are displayed alongside these Grad-CAM overlays, where high-intensity blue and green regions visually indicate the areas of significant interest for the model when classifying COVID-19, Normal, and Pneumonia cases.

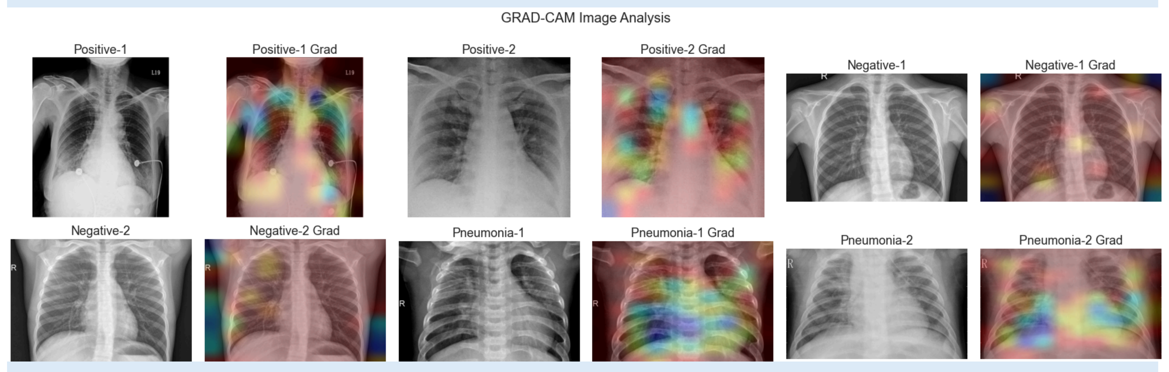


Figure 6: **Grad-CAM Image Analysis**

User Interface

An interactive web-based interface was developed using Streamlit and TensorFlow to allow real-time classification of chest X-ray images. Users can upload an image and receive immediate predictions across three categories:
COVID-19, Pneumonia, and Normal.
The interface displays the predicted class along with a confidence score breakdown. This facilitates transparency and enhances usability for clinical settings.

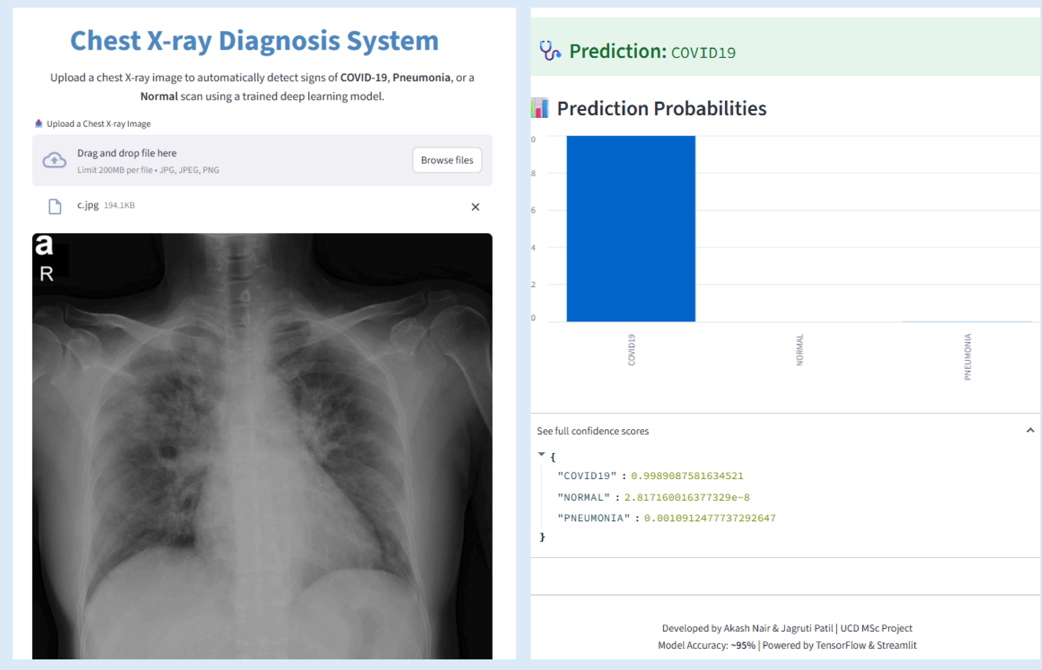


Figure 7: **Interactive diagnostic interface built with Streamlit**

Conclusion And Future Scope

A reliable and automatic mechanism for COVID-19 diagnosis is presented, utilizing chest radiography images to differentiate between patients with pneumonia and COVID-19 infections. This system incorporates image enhancement techniques to improve X-ray intensity and eliminate noise. Notably, the proposed model demonstrates significant strengths, surpassing existing benchmarks as evidenced by its robust classification performance, and is capable of assessing newly acquired clinical data.

However, despite such advancements, AI applications in radiological imaging often face inherent limitations due to insufficient public dataset size and quality, potentially introducing bias. To truly advance this field, establishing systematic data review processes and fostering close collaboration between computational and clinical experts are crucial for developing high-quality, clinically translatable AI solutions.

References:

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