INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 09 ISSUE: 12 | DEC - 2025 SJIF RATING: 8.586 ISSN: 2582-3930

Efficient Detection of COVID-19 and Pneumonia from Chest X-ray Images Using Deep Learning Techniques

1st Assistant Prof. A. V. Kolaki
Department of Electronic and Communication
KLS Vishwanathrao Deshpande Institute of Technology
Haliyal
avkolaki@klsvdit.edu.in

2nd Ms. Priyanka S Hiremath
Department of Electronic and Communication
KLS Vishwanathrao Deshpande Institute of Technology
Haliyal
priyankahiremath11@gmail.com

3rd Ms. Priya Gingaigol
Department of Electronic and Communication
KLS Vishwanathrao Deshpande Institute of Technology
Haliyal
priyaginagaigol@gmail.com

4th Ms. Sakshi S Hiremath
Department of Electronic and Communication
KLS Vishwanathrao Deshpande Institute of Technology
Haliyal
hiremathsakshi30@gmail.com

5th Ms. Tulasa Shivanand Patil
Department of Electronic and Communication
KLS Vishwanathrao Deshpande Institute of Technology
Haliyal
patiltulasa11@gmail.com

Abstract* – Respiratory diseases such as COVID-19 and pneumonia remain a significant global health challenge, particularly in developing regions where access to experienced radiologists is limited. Chest X-ray (CXR) imaging is one of the most widely used diagnostic tools, but manual interpretation is time-consuming and prone to inconsistencies. This paper presents an integrated offline deep-learning system for automatic classification of CXR images into three categories—COVID-19, Pneumonia, and Normal. The proposed framework combines a lightweight Convolutional Neural Network (CNN) for classification and a U-Net architecture for lung segmentation to enhance interpretability. A desktop-based Tkinter GUI is designed to display the prediction, confidence scores, lung mask overlay, and diagnostic suggestions, along with a text-to-speech feature. Experiments on a publicly available Mendeley dataset demonstrate that the model achieves an accuracy of approximately 90%. The system functions entirely offline, making it suitable for rural healthcare environments and emergency screening applications.

Keywords*— COVID-19, Pneumonia, Chest X-ray, Deep Learning, CNN, U-Net, Image Segmentation, Healthcare AI, Computer-Aided Diagnosis, Tkinter GUI.

I. INTRODUCTION

Respiratory infections continue to impose substantial burdens on healthcare systems globally. COVID-19, caused by SARS-CoV-2, exposed the critical need for fast and reliable diagnostic tools. Although the gold standard for COVID-19 detection is the RT-PCR test, limitations such as testing delays, false negatives, and inadequate availability during peak outbreaks highlight the importance of alternative diagnostic solutions.

Chest X-ray imaging is widely available, low-cost, and commonly used to diagnose pneumonia and related lung conditions. However, manual interpretation requires specialized expertise and may vary between radiologists. Artificial Intelligence (AI) and deep learning—particularly Convolutional Neural Networks (CNNs)—have shown tremendous promise in analyzing medical images by automatically learning patterns and abnormalities.

This paper aims to:
• Develop an offline CNN-based classifier for identifying COVID-19, Pneumonia, and Normal lung conditions.
• Integrate a U-Net–based segmentation model to highlight lung regions and improve model transparency.
• Deploy the system through a user-friendly desktop GUI for real-time clinical use.

The proposed system is efficient, interpretable, and fully operational without internet connectivity, making it ideal for low-resource healthcare settings.

II. LITERATURE REVIEW

Several researchers have studied automated COVID-19 detection using deep learning. Early works relied heavily on transfer learning with pretrained networks like VGG16, ResNet50, and MobileNetV2.
These models delivered good results but required high computational power, making them unsuitable for offline clinical use in resource- constrained environments.

More advanced models introduced multi-stage pipelines, including segmentation and classification. U-Net became a popular choice for lung segmentation, as it preserved spatial information through skip connections. Researchers found that classification accuracy significantly improved when lung segmentation was included.

However, most studies either focused only on classification without interpretability, required GPU-based inference, or depended on online cloud APIs.

The system proposed in this work addresses these limitations by using lightweight models suitable for CPU-only systems, integrating segmentation for interpretability and enabling 100% offline execution.

This makes the system practical for real-world healthcare applications.

III. METHODOLOGY

The complete system architecture consists of three integrated components:
• Classification Model (CNN)
• Lung Segmentation Model (U-Net)
• Graphical User Interface (GUI)

The workflow ensures that both classification and segmentation are performed simultaneously for a complete diagnostic output.

A. Overall Workflow

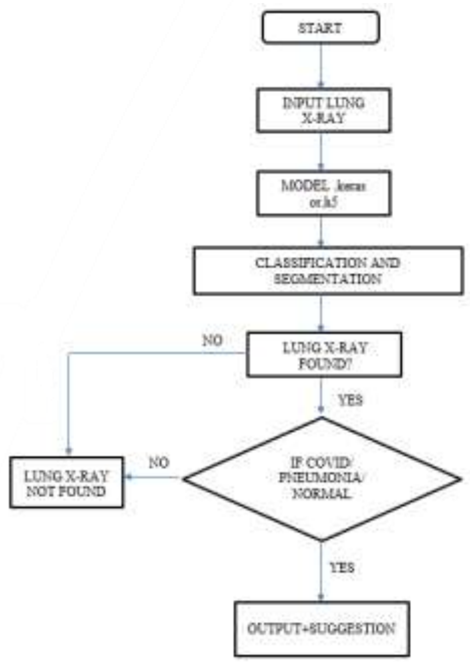

FIGURE 1. FLOW CHART

• A CXR image is uploaded through the GUI.
• Preprocessing (resizing, normalization) is applied.
• The image is sent simultaneously to :Classification model, Segmentation model.
• The CNN outputs class probabilities.
• The U-Net produces a lung mask, which is cleaned using morphological operations.
• The mask is overlaid on the original X-ray image.
• The GUI displays class, confidence scores, diagnosed condition, and suggestions.
• Optional text-to-speech generates an audio output of the diagnosis.

IV. CLASSIFICATION MODEL

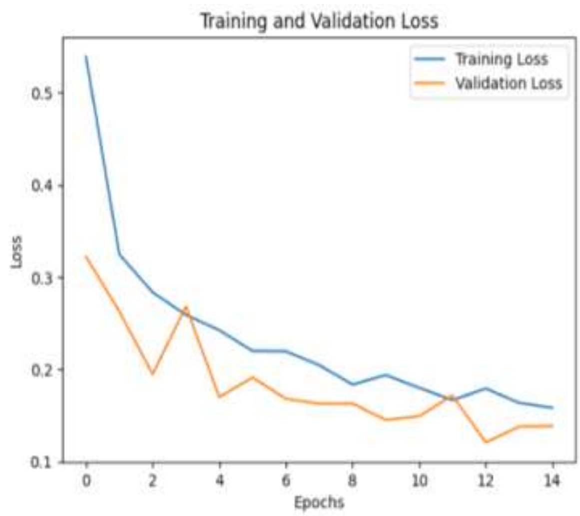

FIGURE 2. TRAINING/VALIDATION LOSS GRAPH

A. Preprocessing

• Images resized to 224×224 or 256×256

- Pixel values normalized to [0, 1]
- Noise removal
- Conversion to grayscale or 3-channel format depending on model requirements

B. Data Augmentation

To improve generalization and avoid overfitting, the following transformations were applied:

- Rotation (±10°)
- Zoom (0.1–0.2 range)
- Horizontal and vertical shifts
- Brightness variation
- Horizontal flips

C. CNN Architecture

```
33/33 ━━━━━━━━━━━━━━━━━━━━ 10s 283ms/step
Confusion Matrix:
 [[310  11   5]
 [  1 358   2]
 [  4  28 328]]
              precision    recall  f1-score   support

       COVID       0.98      0.95      0.97       326
      NORMAL       0.90      0.99      0.94       361
   PNEUMONIA       0.98      0.91      0.94       360

    accuracy                           0.95      1047
   macro avg       0.95      0.95      0.95      1047
weighted avg       0.95      0.95      0.95      1047
```

FIGURE 3. CONFUSION MATRIX OF MODEL

The model consists of:

- Multiple Conv2D layers with ReLU activation
- Max-pooling layers
- Batch normalization
- Flatten layer
- Dense layers with dropout
- Softmax output layer with three neurons

Training settings:

- Loss function: Categorical Cross-Entropy
- Optimizer: Adam
- Early stopping: Enabled
- Batch size: 16–32

```
[5]: model.evaluate(val_generator)

     33/33 ━━━━━━━━━━━━━━━━━━━━ 9s 272ms/step - auc_2: 0.9941 - loss: 0.1385

[5]: [0.13851957023143768, 0.9940553307533264]
```

FIGURE 4. MODEL EVALUATION

The final trained model is saved as a .keras file and loaded during GUI execution.

V. CNN CLASSIFICATION MODEL

The CNN architecture is designed to be lightweight, efficient, and suitable for CPU-based deployment.

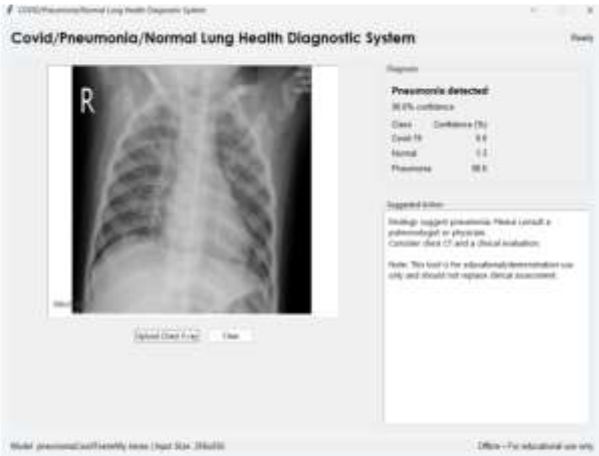

FIGURE 5. GRAPHICAL USER INTERFACE OF CNN CLASSIFICATION MODEL

A. Architecture Overview

The model consists of:

- Convolutional layers: Extract edge-level and texture-level features
- ReLU activations: Add non-linearity
- Batch normalization: Accelerate training
- Max-pooling layers: Reduce spatial dimensions
- Flatten layer: Convert feature maps into a vector
- Dense layers: Learn high-level representations
- Dropout: Prevent overfitting
- Softmax output layer: Predict three classes

B. Training Strategy

- Loss function: Categorical Cross-Entropy
- Optimizer: Adam
- Learning rate: 0.001
- Early stopping: Prevents overfitting
- Epochs: 25–50 depending on convergence

VI. LUNG SEGMENTATION MODEL

A U-Net architecture is used to extract the lung region and eliminate irrelevant background structures such as ribs and shoulders.

A. Preprocessing

- Conversion to grayscale
- Resizing to 512×512
- Normalization
- Reshaping into 4D tensor format

B. Postprocessing

- Thresholding the probability mask

• Morphological opening and closing

• Extraction of the two largest connected components (lungs)
• Matching mask dimensions to the original image.

VII. COMBINED SYSTEM ARCHITECTURE

The segmentation and classification models work in parallel threads to reduce processing time.

FIGURE 6. GRAPHICAL USER INTERFACE OF COMBINED MODEL

The system outputs:

• Prediction: COVID-19 / Pneumonia / Normal
• Confidence percentages
• Segmented lung overlay
• Diagnostic message
• Optional audio output

This design enhances both interpretability and usability.

VIII. DATASET

The dataset is sourced from the Mendeley Data Repository and includes three categories:

• COVID-19
• Pneumonia
• Normal

Each category contains several thousand X-ray images.
The dataset is divided into:

• Training set
• Validation set
• Test set (optional)

Segmentation was either trained using an annotated dataset or a pre-trained model.

XI. GUI IMPLEMENTATION

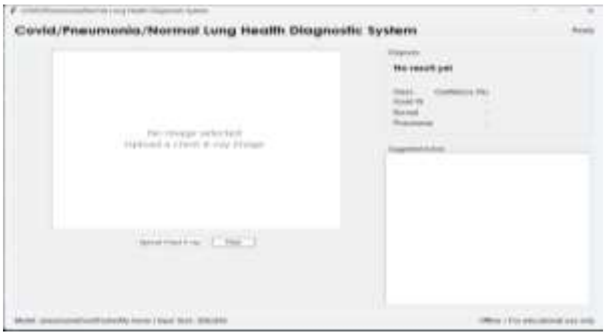

FIGURE 7. GRAPHICAL USER INTERFACE OF COVID/NORMAL/PNEUMONIA LUNG DIAGNOSTIC SYSTEM

The Tkinter-based GUI includes:
• File Upload Section
• Prediction Display Box
• Confidence Score Display
• Segmented Lung Overlay Viewer
• Suggestion/Recommendation Box
• Text-to-Speech Button
• Offline Mode Support

The GUI is designed to be simple, intuitive, and suitable for undergraduate projects and medical demonstrations.

X. RESULTS AND DISCUSSION

The CNN achieved approximately 90% validation accuracy.

Observations:

• COVID-19 and Normal classes were detected with high precision.
• Slight confusion between severe pneumonia and COVID-19 due to structural similarities.
• Segmentation significantly improved interpretability of predictions.

The system performed efficiently on CPU-only systems, confirming suitability for low-resource deployments.

XI. ADVANTAGES

• Fully offline functionality
• High interpretability due to segmentation
• Fast predictions suitable for emergency screening
• User-friendly GUI
• Low computational demand
• Accessibility through text-to-speech

XII. FUTURE SCOPE

• Integration with hospital PACS systems
• Addition of diseases like TB, COPD, lung cancer
• Deployment on smartphones

- Cloud-based multi-hospital training
- Integration of Grad-CAM or SHAP-based explainability
- Real-time X-ray streaming analysis

XIII. CONCLUSION

This research presents a deep-learning–powered classification and segmentation system for detecting COVID-19 and pneumonia using chest X-rays. The lightweight CNN classifier and U-Net segmentation network significantly enhance diagnostic accuracy and interpretability. The Tkinter GUI allows practical deployment in rural hospitals and screening centers. With approximately 90% accuracy and complete offline performance, the system shows strong potential as a reliable computer-aided diagnosis tool.

REFERENCES

[1] J. P. Cohen, P. Morrison, and L. Dao, “COVID-19 Image Data Collection,” arXiv preprint arXiv:2003.11597, 2020.

[2] O. Ronneberger, P. Fischer, and T. Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation,” MICCAI, 2015.

[3] Mendeley Data Repository, “COVID-19 and Pneumonia Chest X-ray Dataset,” 2020.