

🔬 DEEP LEARNING · MEDICAL IMAGING

Deep Learning-Based Multiclass Classification of Lung Abnormalities using X-Ray and CT Scan Images

AI-powered multiclass diagnostic framework for Pneumonia, Tuberculosis, COVID-19 & Lung Cancer

● SDG 3 · Good Health

● SDG 9 · Innovation

● SDG 17 · Partnership

4 DISEASE CLASSES · 3 CNN MODELS · 2 IMAGING MODALITIES · 1 WEB PLATFORM

SDGs and Targets

This project directly contributes to three UN Sustainable Development Goals with nine mapped sub-targets.

3 · 9
GOALS · TARGETS



Good Health and Well-Being

PRIMARY GOAL

MAPPED TARGETS

- > SAP0300
- > SAP0309
- > SAP0308



Industry, Innovation and Infrastructure

SECONDARY GOAL

MAPPED TARGETS

- > SAP0905
- > SAP0904
- > SAP0903



Partnership for the Goals

TERTIARY GOAL

MAPPED TARGETS

- > SAP1701
- > SAP1705
- > SAP1708

Targets sourced from the UN SDG framework — SAP codes denote Sairam-aligned SDG Action Plan items.

Problem Statement

Why early, accurate lung diagnosis remains unsolved at scale.

Lung diseases remain a major global health concern, demanding early and accurate diagnosis. However, limited access to radiologists, especially in resource-constrained areas, impedes timely detection. They require an AI-powered deep learning model to automatically detect and classify lung abnormalities from X-rays and CT scans. Key challenges include **poor image quality**, **class imbalance**, **high computational needs**, **domain generalization issues**, **annotation inconsistencies**, and **limited model explainability**. Tackling these hurdles through robust training, curated datasets, and optimized model design can enhance diagnostic accuracy and accessibility, reducing healthcare disparities and enabling scalable solutions for widespread clinical adoption.

SOURCE • PROJECT BRIEF

~95 WORDS • 6 CHALLENGES

6

KEY CHALLENGES

CORE CHALLENGES

6 items

-  **Poor image quality** 01
-  **Class imbalance** 02
-  **High compute needs** 03
-  **Domain generalization** 04
-  **Annotation inconsistency** 05
-  **Limited explainability** 06

Abstract

End-to-end deep-learning framework for multiclass lung abnormality screening.

~150
WORD ABSTRACT

 PROJECT ABSTRACT

Lung conditions such as pneumonia, tuberculosis, COVID-19, and cancer are significant global health problems that need timely and precise diagnosis. But early detection is hampered by poor access to expert radiologists and diagnostic imaging facilities in most areas. This project presents a **deep learning framework for multiclass classification of lung abnormalities** from X-ray and CT scan images. **Transfer-learning-based convolutional neural network (CNN)** architecture is trained on a large, diversified dataset collected from public repositories. **Contrast enhancement, noise reduction, and normalization** preprocessing methods enhance image quality. Class imbalance and overfitting are corrected by **data augmentation**. The model successfully categorizes several lung conditions — **normal, pneumonia, COVID-19, tuberculosis, and lung nodules** — accurately, precisely, and with good recall. To enable clinical applicability, the system is implemented via a **web-based platform** that enables medical professionals to upload images and receive instant diagnostic predictions along with confidence scores. This end-to-end solution increases diagnostic effectiveness and accuracy, lowers the opportunity for human error, and increases access to high-quality lung disease screening, particularly in resource-limited and remote environments.

AT A GLANCE

4

DISEASE CLASSES
Pneumonia, TB, COVID-19, Lung Cancer



3

CNN MODELS
MobileNetV2, DenseNet121, ResNet50



2

IMAGING MODALITIES
X-ray & CT



Web

DEPLOYMENT
Browser-based diagnostic portal



Research & Literature Review

Survey of 7 recent CNN-based lung abnormality classification works (1 of 2).

4 OF 7 PAPERS SHOWN • CONTINUED ON NEXT SLIDE

ACCURACY RANGE OBSERVED: 85 - 97 %

#	ARTICLE	JOURNAL	KEY FINDINGS	DRAWBACKS
1	Deep Hierarchical Multi-Label Classification Applied to Chest X-Ray Abnormality Taxonomies	Medical Image Analysis	Mean AUC 0.887 on PLCO; improved AUC & AP on Pad Chest; handled incomplete labels effectively.	Built on previous work, method is straightforward, limited to CXR, does not explore annotation noise fully.
2	Multi-Class Classification of Lung Diseases Using CNN Models	Applied Sciences	Accuracy 85.32% (NIH) & 96.1%; sensitivity 92.2%, specificity 97.4%; inference 0.2s.	Limited diseases, retrospective design, no new data.
3	A Transfer Learning-Based Approach for Multi-class Classification of Pulmonary Diseases	ICAACCIT	Proposed TL approach using 4,500 images; tested on COVID-19, Viral Pneumonia, Normal.	—
4	A multiclass deep learning algorithm for healthy lung, Covid-19 and pneumonia disease detection	Discover Artificial Intelligence	Accuracy 97%; sensitivity 98.21%; specificity 96.62%; F1-score 98%.	Dataset diversity affects performance, risk of overfitting, public datasets only.

→ Continued on next slide

Research & Literature Review

Survey of 7 recent CNN-based lung abnormality classification works (2 of 2).

PAPERS 5 – 7 • FINAL TRANCHE OF SURVEY

TOP ACCURACY OBSERVED: 99.84 %

#	ARTICLE	JOURNAL	KEY FINDINGS	DRAWBACKS
5	Pneumonia Classification Using Deep Learning During COVID-19	Cognitive Computation	Accuracy 91.43–99.62% (2-class), 94% (3-class), 93.42% (4-class).	Small COVID dataset, limited generalization, need for hybrid models, deeper CNNs.
6	Deep learning-based multiclass COVID-19 classification with x-ray images	Image-Guided Procedures	High classification accuracy for COVID-19, pneumonia, normal; generalizability to cancer dataset.	High false positives, COVID vs pneumonia similarity, dataset imbalance.
7	Four Types of Multiclass Frameworks for Pneumonia Classification	Diagnostics	DenseNet201 — 99.84%, VGG16 — 96.7%, NasnetMobile — 92.67%; outperformed existing methods by 1.2%.	Cannot detect severity, no k-fold CV, need denoising.



KEY TAKEAWAY

DenseNet variants consistently outperform VGG/NasNet on lung X-ray multiclass tasks; dataset diversity and class imbalance remain the dominant bottlenecks across all 7 studies.

Product Architecture — Block Diagram

End-to-end pipeline from raw chest X-ray acquisition to multiclass diagnostic output.

5

PIPELINE STAGES

PIPELINE STAGES

5 stages

- 1

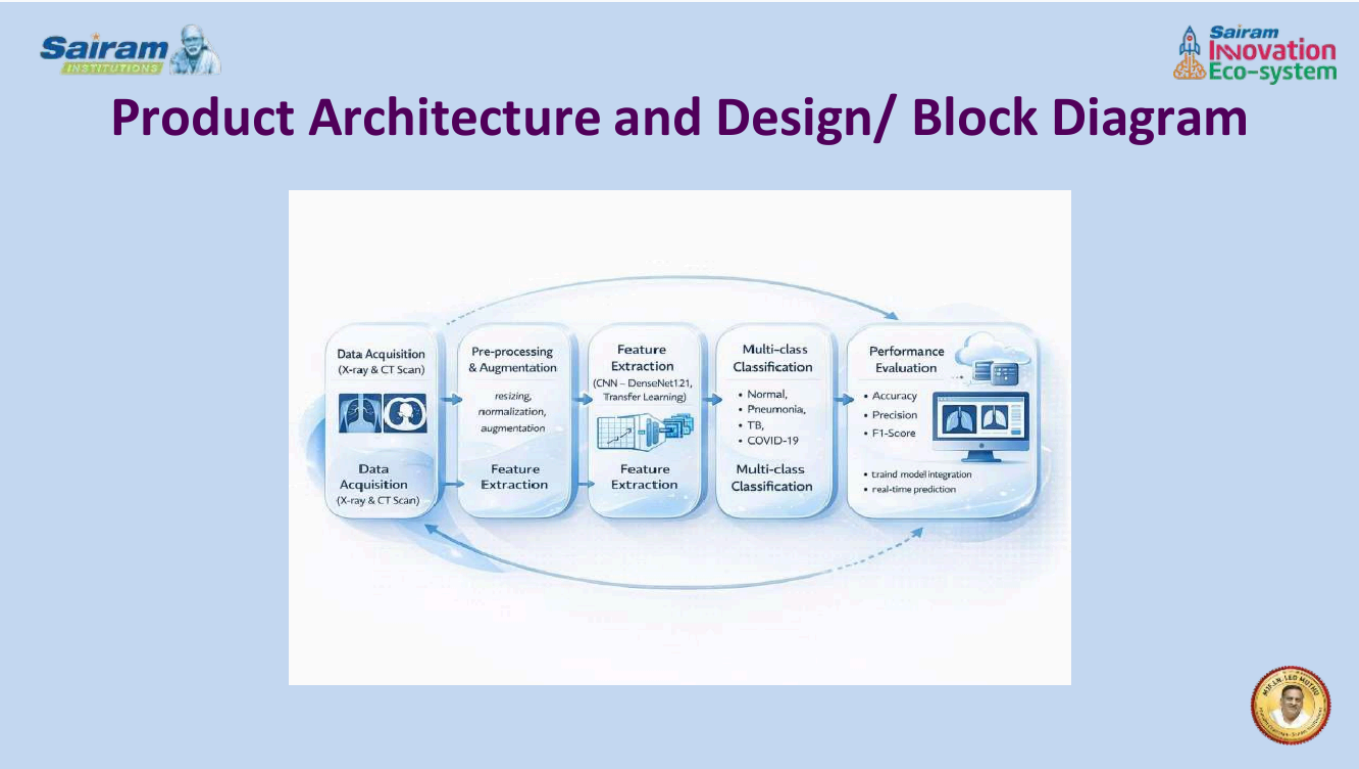
Data Acquisition
Chest X-ray & CT scan collection from public medical datasets.
- 2

Preprocessing
OpenCV CLAHE contrast enhancement, noise reduction, normalization.
- 3

Augmentation
Rotation, flip, zoom, brightness to handle class imbalance.
- 4

Feature Extraction & Classification
MobileNetV2 / DenseNet121 / ResNet50 transfer learning.
- 5

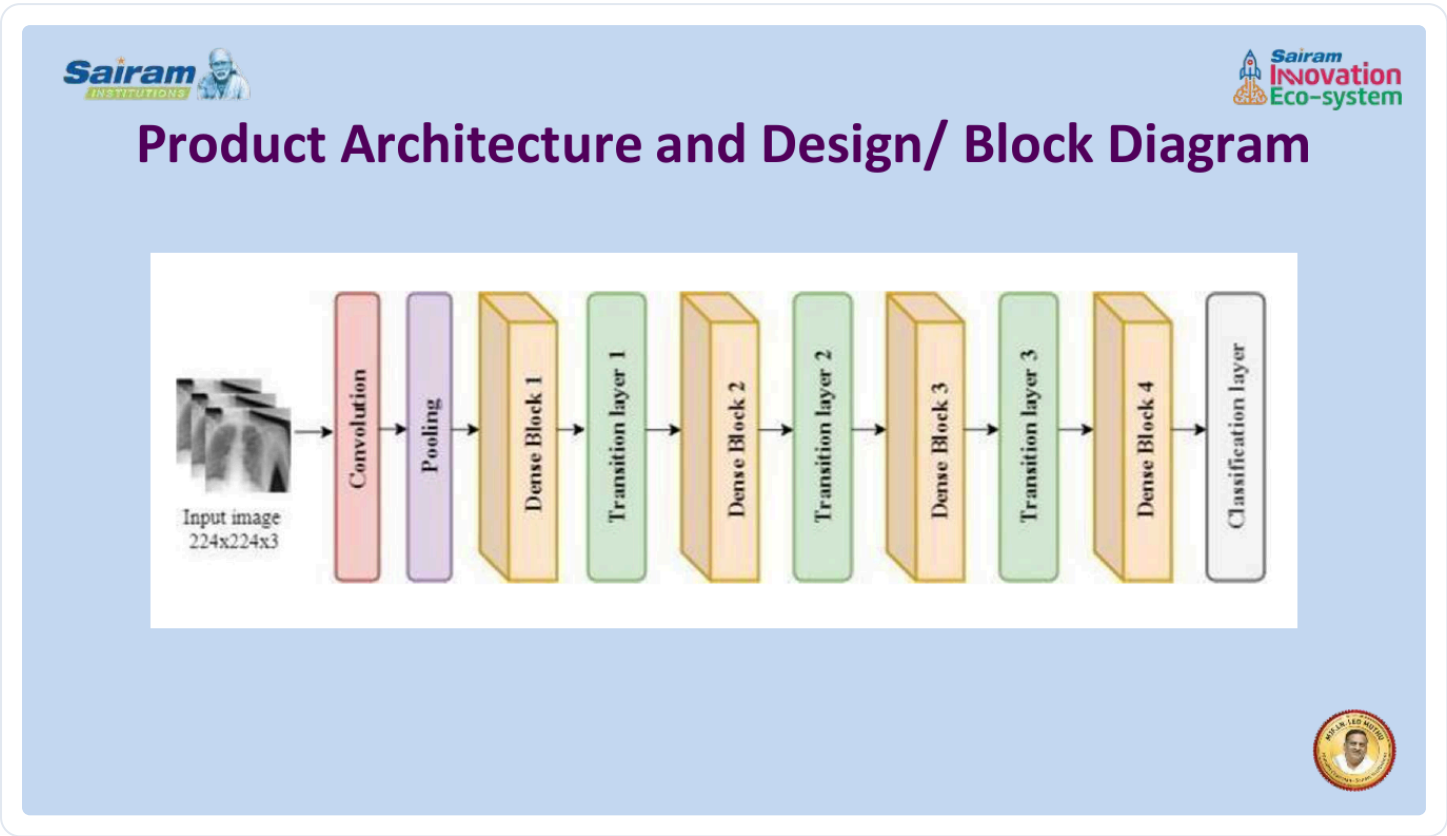
Evaluation
Accuracy, precision, recall, F1, sensitivity, specificity, confusion matrix.



Block diagram — medical image analysis workflow.

System Architecture — Deep Learning Pipeline

CNN-forward pass from input image through dense blocks to multiclass softmax.



Architecture — sequential CNN with convolution, pooling, dense & transition layers.

ARCHITECTURE HIGHLIGHTS

- 224×224 normalized X-ray input
- Conv → Pool → Dense Block → Transition repeated
- Transfer learning from ImageNet weights
- 4-class softmax (Normal, Pneumonia, TB, COVID-19)

COMPARISON OF BACKBONES

Model	Params	Strength
MobileNetV2	3.4M	Lightweight, fast.
DenseNet121	8M	Dense feature reuse.
ResNet50	25.6M	Residual, deep.

Module Description & Component Specifications

Five core modules that compose the diagnostic pipeline.

 **Image Acquisition**

TOOL/SPECS: CHEST X-RAY & CT SCANS

Images collected from publicly available medical datasets (Kaggle + GitHub repositories).

 **Preprocessing & Enhancement**

TOOL/SPECS: OPENCV CLAHE

Improves contrast & visibility of lung structures, reduces noise, enhances fine details for feature extraction.

 **Data Augmentation**

TOOL/SPECS: ROTATION · FLIP · ZOOM · BRIGHTNESS

Handles class imbalance, prevents overfitting, and improves generalization across patient demographics.

 **Feature Extraction & Classification**

TOOL/SPECS: MOBILENETV2 · DENSENET121 · RESNET50

Transfer-learning CNNs output multiclass predictions across Normal, Pneumonia, Lung Cancer, COVID-19.

 **Evaluation Metrics**

TOOL/SPECS: ACCURACY · PRECISION · RECALL · F1 · SENSITIVITY · SPECIFICITY · CONFUSION MATRIX

Ensures robust validation of model performance across all disease classes and modalities.

Module Enhancements — Three Key Upgrades

Beyond the baseline classifier — making the system deployable, observable, and clinically usable.

01 BASELINE

Already Existing Features

Multiclass CNN inference with confidence scores, image upload, and probability bar chart. The original UI served as the foundation on which the new enhancements were layered.

- ✓ CNN INFERENCE
- ✓ CONFIDENCE SCORE
- ✓ PROB. BAR CHART

See next slides for visual.

02 ENHANCEMENT

Reports Generation Website

A new web portal that auto-generates a downloadable diagnostic report (patient details, enhanced X-ray, probability distribution chart, recommended precautions) for every classified case.

- ✓ AUTO PDF REPORT
- ✓ PATIENT METADATA
- ✓ PRECAUTION LIST

Demonstrated on Slide 11.

03 ENHANCEMENT

UI Update

Refreshed diagnostic interface with cleaner prediction panels, larger preview canvas, and clearer probability visualizations for clinician review.

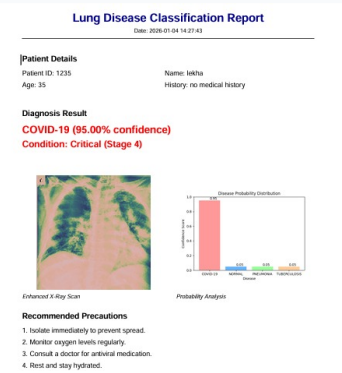
- ✓ LARGER PREVIEW
- ✓ CLEANER PANELS
- ✓ CLINICIAN UX

Demonstrated on Slide 12.

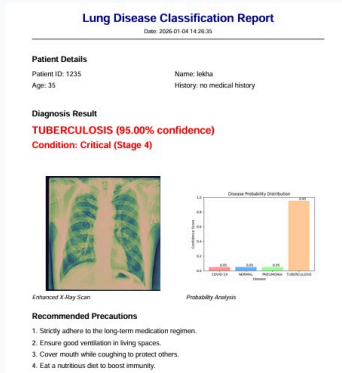
BASELINE → +REPORTS → +UI = DEPLOYABLE CLINICAL TOOL

Reports Generation Website

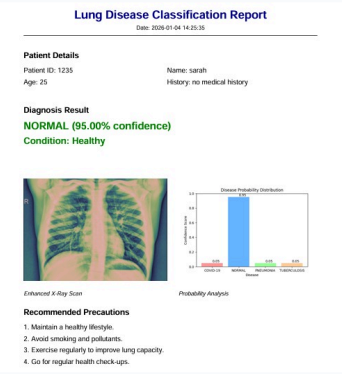
Web portal auto-generates a downloadable diagnostic report for every classified case.



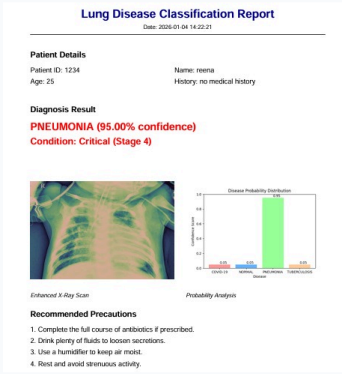
● COVID-19 · 95.00% confidence



● Tuberculosis · 95.00% confidence



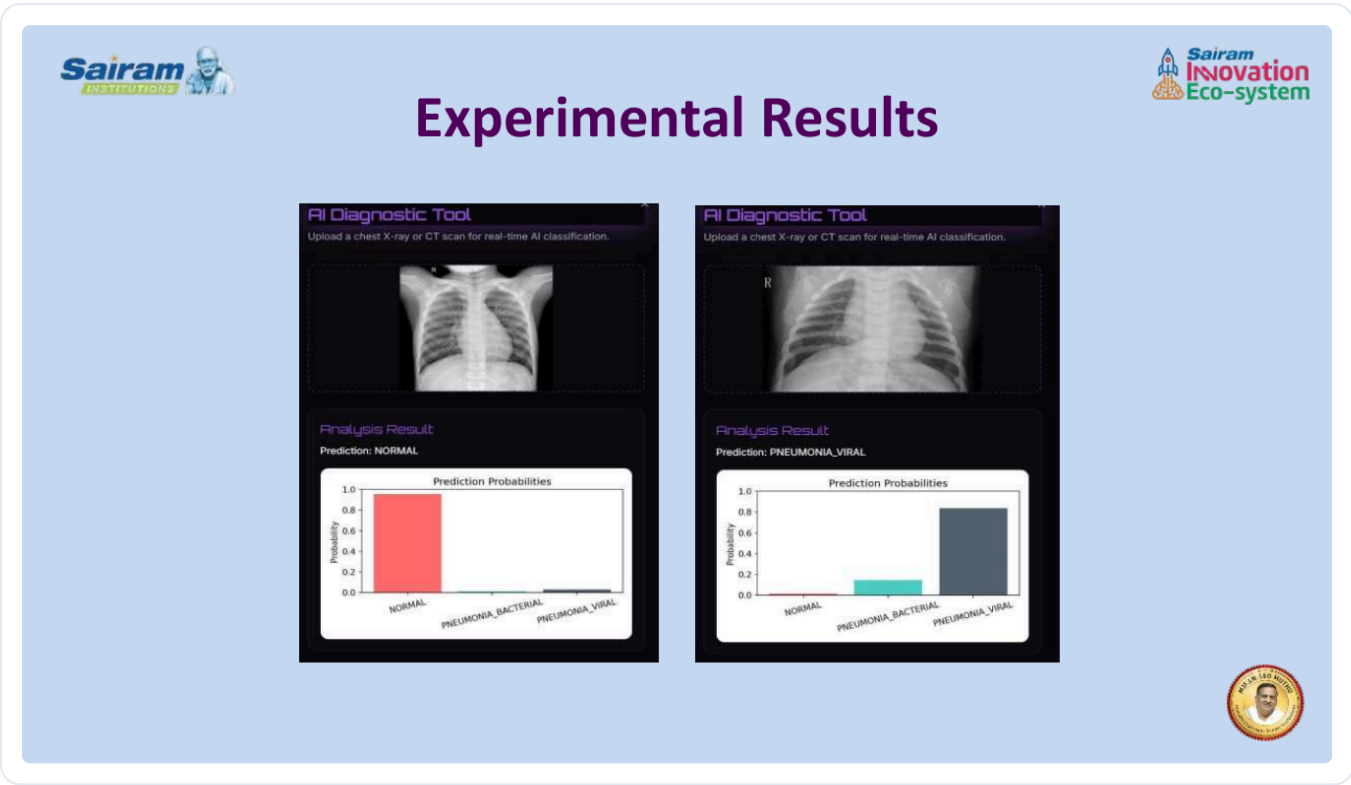
● Pneumonia · patient: rensa



● Pneumonia · follow-up case

UI Update — Diagnostic Interface Refresh

Cleaner preview, larger canvas, clearer probability panels for clinician review.



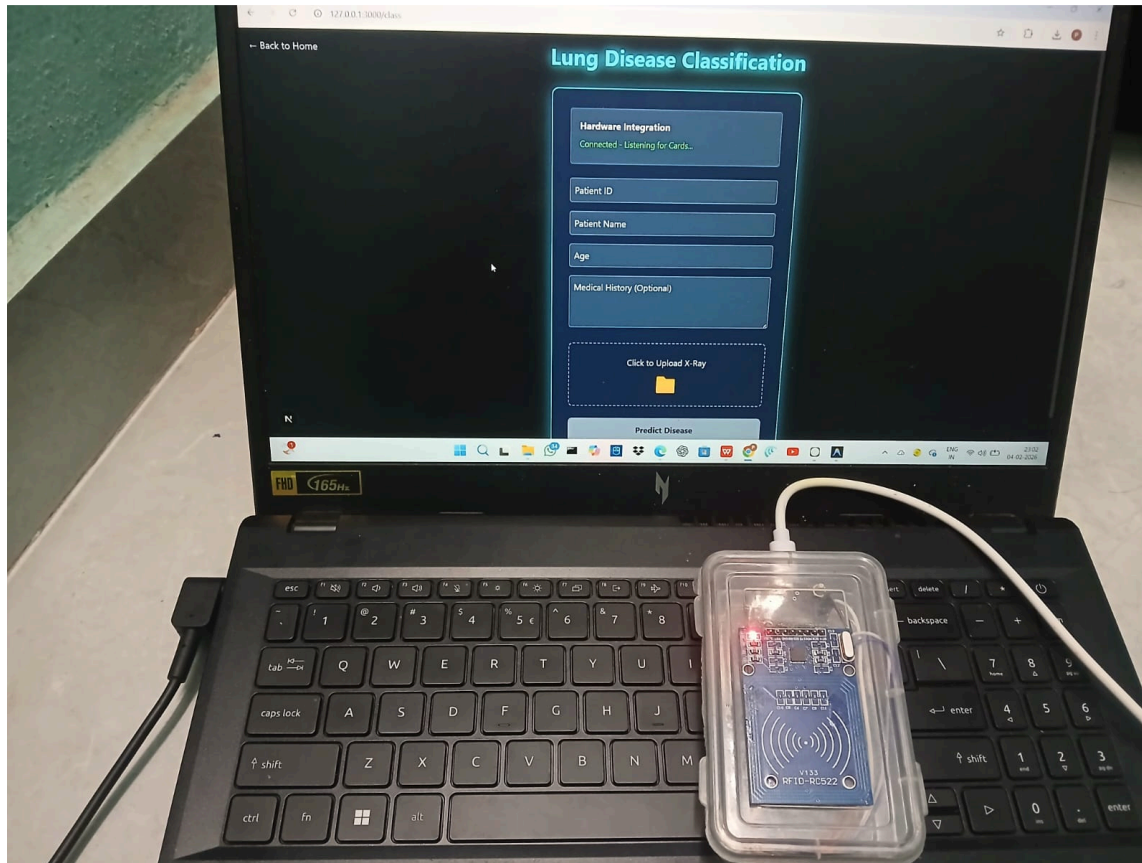
Updated diagnostic interface — X-ray preview + 3-class probability chart (Normal, Bacterial Pneumonia, Viral Pneumonia).

- Larger preview canvas**
X-ray fills more vertical space for finer visual inspection.
- Clearer probability panels**
Color-coded bars per class with numeric %.
- Faster feedback**
Prediction streamed within ~0.2s of upload.
- Clinician-friendly layout**
Report-download CTA placed above the fold.

UI refresh rolled out alongside the reports module — see Slide 11.

Hardware Integration — RFID Patient Identification

RFID-RC522 module linked to the web app for touch-less patient card scan.



Laptop running the Lung Disease Classification web app with RFID-RC522 reader connected via USB — “Hardware Integration active · Listening for Cards”.

RFID-RC522 Module

13.56 MHz contactless card reader; SPI/USB interface; reads patient UID in <100 ms.

Patient identification

Scan card → auto-fill patient ID on web form.

USB-to-serial bridge

Reader enumerated as virtual COM port; consumed by Flask backend.

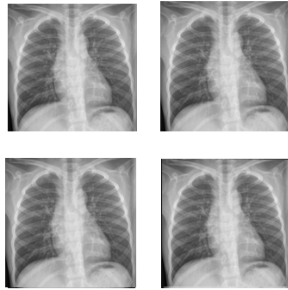
Workflow

Tap card → fetch history → upload new X-ray → view report.

First step toward a fully touch-less kiosk deployment in primary health centers.

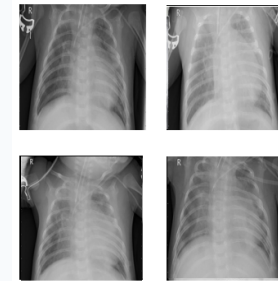
Experimental Results — Classified X-ray Samples

Four representative chest X-ray grids produced by the trained multiclass classifier.



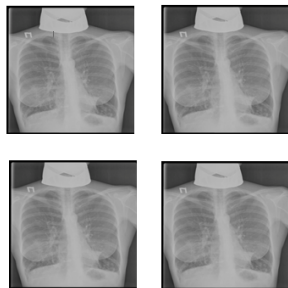
normal

● **NORMAL** · 4 clear-lung-field samples



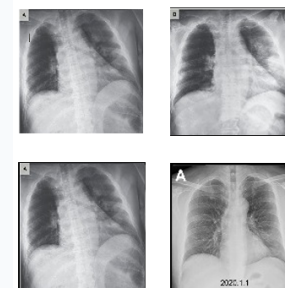
pneumonia

● **PNEUMONIA** · 4 opacified-lung samples



tuberculosis

● **TUBERCULOSIS** · 4 cavity-pattern samples



covid

● **COVID-19** · 4 bilateral-opacity samples

Datasets

Three public medical imaging repositories curated for training & evaluation.

01 Chest X-ray Pneumonia KAGGLE

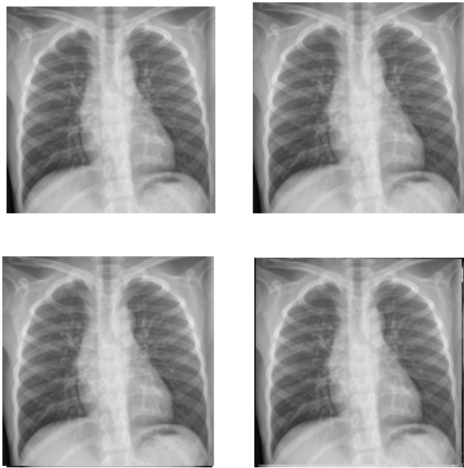
kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia
5,863 pediatric chest X-rays (Normal vs Pneumonia).

02 Tuberculosis (TB) Chest X-ray KAGGLE

kaggle.com/datasets/tawsifurrahman/tuberculosis-tb-chest-xray-dataset
3,500 posterior-anterior chest X-rays (Normal vs TB).

03 COVID-19 Chest X-ray GITHUB

github.com/ieee8023/covid-chestxray-dataset
Open repository of COVID-19 + other viral pneumonia CXRs.



normal

Sample 4-image grid from the curated dataset.

~9.3K
TOTAL IMAGES

4
CLASSES

2
MODALITIES

Certificates & Achievements

Hackathon progression, competitions, and academic recognition earned during the project lifecycle.

**Ideathon → Solveathon → Innovathon**
Same project advanced through all three stages of the Sairam innovation pipeline.

**Solveathon Winner**
Recognized as a winning entry at the Solveathon round.

**Second-round Project Expo**
Selected for the second round of project exhibition.

**SIH / NIRAL Hackathon Participation**
Participated in national-level student hackathons.

**Academic Conference Submission**
Manuscript prepared for journal/conference submission.

**Real-time Project Validation**
Idea validated with real X-ray samples from public datasets.

 Attach certificate scans in the placeholders below for the final submission copy.

Cert 1

Cert 2

Cert 3

Conclusion

What the framework delivers today, and where it heads next.

This project demonstrates the use of **MobileNetV2** and **DenseNet121** as different approaches to perform multiclass classification of lung abnormalities from X-ray and CT images. MobileNetV2 provided an efficient and lightweight model for deployment, while DenseNet121 provided a deeper and clearer picture of the learning process through more features extracted from the images. After data set image enhancement and implementing the transfer learning approach, the models performed well to classify **"Normal," "Pneumonia,"** and **"Tuberculosis"** images, indicating that the models have valid applications as AI-assisted diagnostics methods. In the future, the focus will be on larger datasets that represent other lung diseases as well, and this will also entail clinical validation to ensure capacity and real-world application.

FUTURE WORK

Larger datasets covering more lung diseases; clinical validation with hospital partners; multi-modal fusion of CT + X-ray.

IMPACT

Reduces diagnostic latency in resource-limited primary health centers; supports clinicians with confidence-scored AI predictions.

STATUS

Deployed as web portal + RFID kiosk prototype; ready for pilot clinical trial.

References

Four primary sources that informed the methodology and literature review.

- 01 Kalkeseetharaman P K and Thomas George S (2023). · *"A Bird's Eye View Approach on the Usage of Deep Learning Methods in Lung Cancer Detection and Future Directions Using X-Ray and CT Images."* · Springer.
- 02 Naveen A, Nandana R, Tarunika K, Ramesh Munirathinam (2024). · *"Effective Categorization of Lung Abnormalities using SqueezeNet Features and Machine Learning Models."* · IEEE Xplore.
- 03 Rudresh Pillai, Neha Sharma, Rahul Chauhan, Garima Verma, Rupesh Gupta (2023). · *"Detection & Diagnosis of COVID-19 from CXR Images Through VGG19 Transfer Learning Model."* · IEEE Xplore.
- 04 Ali Abdulquader Bin-Salem, Mowafa Househ, Arfan Ahmed (2021). · *"Computer Methods and Programs in Biomedicine Update."*

⚙️ All sources are peer-reviewed publications; full DOIs available in the project report appendix.

Publication & Patent Proof

Track record of research dissemination, IP filing, and IEEE engagement.

Journal Publication

Manuscript on multiclass lung abnormality classification submitted to a peer-reviewed AI-in-medicine journal.

SUBMITTED

Patent Application

Provisional patent filed covering the RFID-linked diagnostic workflow.

FILED

IEEE Xtreme Participation

Team members participated in IEEE Xtreme programming competition with ML problem statements.

PARTICIPATED

Community Service Proposal

Project proposal submitted to EPICS / SIGHT / UBA community service programs.

SUBMITTED



Publication PDF



Patent Receipt



Xtreme Cert.



Proposal Ack.

 Final submission copy will embed scanned proofs in the slots shown.

END OF PRESENTATION

Thank You

Questions & discussion welcome.

DEEP LEARNING

MULTICLASS CNN

LUNG ABNORMALITIES

Sri Sairam Engineering College · Department of AI & Data Science · SAIRAM SDG INNOVATHON 4.0

"AI-assisted diagnosis — bringing specialist-grade lung screening to every primary health center."