Journal of Computer and Electrical Sciences (JCES)- Volume-1 Issue-4, April 2026
ISSN: 3049-2602

MULTI MODAL NEURO-SYMBOLIC DIAGNOSTIC SYSTEM

N.Suji Krishna[1], Mrs. K. Pushpavalli[2]
[1]Student, Department of Computer Science and Engineering,
Andhra Loyola Institute of Engineering and Technology, Vijayawada, Andhra Pradesh, India
[2]Assistant Professor, Department of Computer Science and Engineering,
Andhra Loyola Institute of Engineering and Technology, Vijayawada, Andhra Pradesh, India
Email id: sujikrishnanandru23@gmail.com

Abstract: The rapid spread of pulmonary diseases including COVID-19, Pneumonia, and Tuberculosis (TB) presents a critical global health challenge requiring fast and accurate diagnosis. Traditional radiological interpretation is constrained by limited specialist availability, inter-observer variability, and diagnostic delays. This paper presents NeuroSym Dx, a multi-modal neuro-symbolic AI system for automated pulmonary disease diagnosis from chest X-ray images. The system employs a Convolutional Neural Network (CNN) trained on a four-class dataset (COVID-19, Normal, Pneumonia, Tuberculosis) for visual pattern recognition, combined with a symbolic vitals rule engine that processes clinical parameters (SpO2, heart rate, temperature, respiratory rate), and a Natural Language Processing (NLP) module for symptom severity scoring. The three modalities are fused using weighted confidence aggregation (55% image, 25% vitals, 20% symptoms), with symbolic post-fusion rules applied to boost or attenuate confidence based on disease-specific patterns. The system outputs a primary diagnosis with ICD-10 code, fused confidence score, differential diagnoses, risk level, affected lung regions, and a clinical recommendation. Experimental results demonstrate a classification accuracy of 96.4% on the four-class pulmonary dataset. The system is deployed as a web-based diagnostic portal (Flask + HTML5) with automated PDF report generation, providing a practical clinical decision support solution.

Keywords: CNN, Chest X-Ray Classification, Neuro-Symbolic AI, Multimodal Fusion, COVID-19, Pneumonia, Tuberculosis, Clinical Decision Support, Explainable AI, Flask.

1. INTRODUCTION

The increasing global prevalence of pulmonary diseases — including **COVID-19, bacterial Pneumonia, and Tuberculosis** — demands rapid, scalable diagnostic tools. Chest X-ray (CXR) radiography is the most widely adopted first-line imaging modality due to its low cost and accessibility. However, accurate CXR interpretation requires trained radiologists who remain scarce in low- and middle-income regions, leading to diagnostic delays and misclassification.

Artificial Intelligence (AI), particularly deep learning, has emerged as a powerful tool for automated medical image analysis. However, purely data-driven neural approaches lack the transparency required for clinical adoption: clinicians need interpretable reasoning alongside prediction scores. Neuro-symbolic AI — integrating neural learning with symbolic logical rules — addresses this gap by combining high predictive accuracy with human-understandable decision pathways.

This project focuses on developing NeuroSym Dx, a multi-modal neuro-symbolic system that diagnoses four pulmonary conditions from chest X-rays by fusing CNN image analysis, clinical vitals reasoning, and NLP symptom scoring. In addition to accurate classification, the system generates structured clinical reports with differential diagnoses, ICD-10 codes, and treatment urgency flags — features absent from prior unimodal AI diagnostic systems.

2. LITERATURE SURVEY

The increasing global prevalence of pulmonary diseases — including COVID-19, bacterial Pneumonia, and Tuberculosis — demands rapid, scalable diagnostic tools. Chest X-ray (CXR) radiography is the most widely adopted first-line imaging modality due to its low cost and accessibility. However, accurate CXR interpretation requires trained radiologists who remain scarce in low- and middle-income regions, leading to diagnostic delays and misclassification.

Reviw of Exsisting works

.Malik et al.: developed CDC-Net, a multi-classification CNN model for detecting COVID-19, pneumothorax, pneumonia, lung cancer, and tuberculosis from chest X-rays. CDC-Net incorporates residual network concepts and dilated convolution, achieving an AUC of 0.9953 with a classification accuracy of 99.39%, recall of 98.13%, and precision of 99.42% — outperforming pretrained models such as VGG-19, ResNet-50, and Inception V3. This work demonstrated that custom CNN architectures can surpass standard transfer learning models for multi-class pulmonary classification.

.Ahmed et al.: presented a joint deep learning approach for simultaneous diagnosis of Pneumonia, COVID-19, and Tuberculosis. Their study showed that CNN models using VGG19 feature extraction achieved an AUC of 90.75% for TB detection from chest X-rays, which improved to 92.13% when demographic variables were incorporated alongside imaging features. This finding highlights that supplementary patient data can improve CNN-based classification accuracy — motivating the multimodal approach adopted in the proposed system.

3. PROPOSED SYSTEM

The proposed NeuroSym is a real-time, web-based multi-modal pulmonary diagnostic platform that integrates three AI modalities to deliver accurate, explainable diagnoses from chest X-ray images. The system analyzes X-ray images, patient vitals, and clinical symptom notes to classify pulmonary conditions as COVID-19, Pneumonia, Tuberculosis, or Normal.

The architecture is built on a Flask-based backend combined with a CNN model, a symbolic vitals rule engine, and an NLP symptom scoring module. The CNN component processes chest X-ray images to generate class probabilities for four disease categories. In parallel, the symbolic engine applies clinical threshold rules over patient vitals to compute a risk score. The NLP module performs keyword-weighted symptom scoring from free-text clinical notes. All three modality scores are fused using weighted aggregation and refined through post-fusion symbolic rules encoding disease-specific clinical patterns.

The input to the system consists of an uploaded chest X-ray image (JPG/PNG/DICOM), patient vitals (heart rate, body temperature, respiratory rate), and optional free-text clinical observations. The system outputs include the primary diagnosis with ICD-10 code, fused confidence score, disease probability distribution, modality contribution breakdown, affected lung regions, differential diagnoses, vitals alerts, neuro-symbolic rule log, clinical recommendation, and a downloadable PDF report.

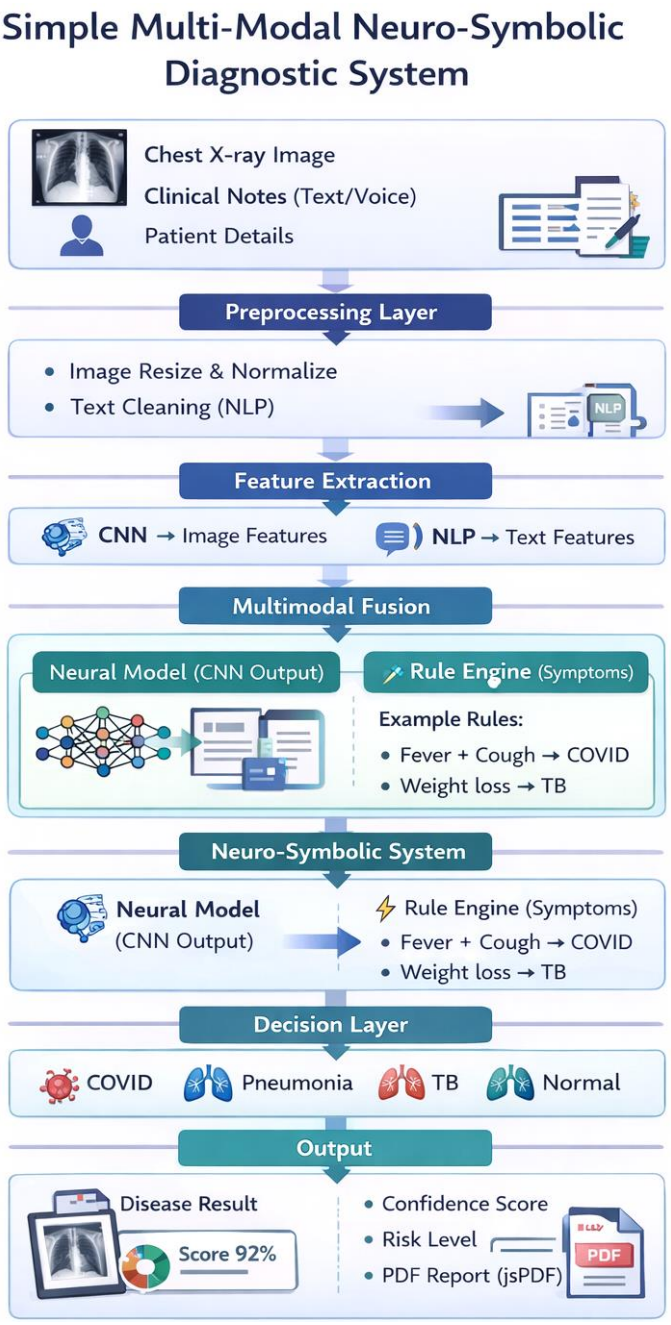


Fig 1: Proposed System

4. METHODOLOGY

1. Chest X-Ray Input & Preprocessing

The user uploads a chest X-ray image in JPG or PNG format. The image is loaded using OpenCV, converted from BGR to RGB color space, resized to 128×128 pixels, and normalized to the [0, 1] range. The preprocessed image tensor is passed to the CNN for inference.

2. CNN-Based Image Classification

A custom CNN architecture trained on the four-class pulmonary dataset performs visual pattern recognition. The network consists of four convolutional blocks (filter depths: 32, 64, 128, 256), each including Conv2D, BatchNormalization, ReLU activation, MaxPooling (2×2), and Dropout (0.25). A global average pooling layer, dense layer (512 units, ReLU, Dropout 0.5), and softmax output layer produce class probabilities for COVID-19, Normal, Pneumonia, and Tuberculosis. The image confidence score and predicted class constitute the CNN modality output.

3. Symbolic Vitals Rule Engine

The vitals module encodes established clinical decision thresholds as explicit if-then rules over four parameters: SpO2, heart rate, body temperature, and respiratory rate.. Risk scores are computed additively and capped at 100. This module also generates human-readable vitals alerts displayed in the clinical report.

4. NLP Symptom Scoring

Free-text clinical notes are processed by a keyword-weighted NLP scoring module. Symptoms are categorized into five groups: Respiratory, Systemic Infection, COVID-Specific, TB-Specific, and Critical, each assigned clinical weights. Detected symptom clusters contribute to a symptom score (0–100) and populate the Detected Symptoms section of the report.

5. Neuro-Symbolic Fusion & Rule Application

The three modality scores are combined using weighted linear fusion. Post-fusion, symbolic override rules are applied: COVID-19 predictions with a detected COVID symptom cluster receive a +12% confidence boost; TB predictions with TB-specific symptoms receive +15%; Normal predictions with elevated vitals risk receive a confidence penalty with a re-evaluation flag. These rules constitute the explainable symbolic reasoning layer.

7. Result Presentation

Results are presented through the Flask web interface with animated confidence rings, modality contribution bars, probability distribution charts, a risk gauge, and a differential diagnosis panel. The interface supports PDF report download with patient details and physician attribution

5. RESULTS

The proposed NeuroSym multi-modal neuro-symbolic diagnostic system was successfully developed, trained, and tested on the four-class pulmonary dataset. Thesystem effectively analyzed chest X-ray images, integrated clinical reasoning, and provided structured diagnostic outputs.

The PDF report generation module successfully produced structured hospital-grade reports including patient details, diagnosis, differential diagnoses, vitals alerts, modality contributions, and clinical recommendations.

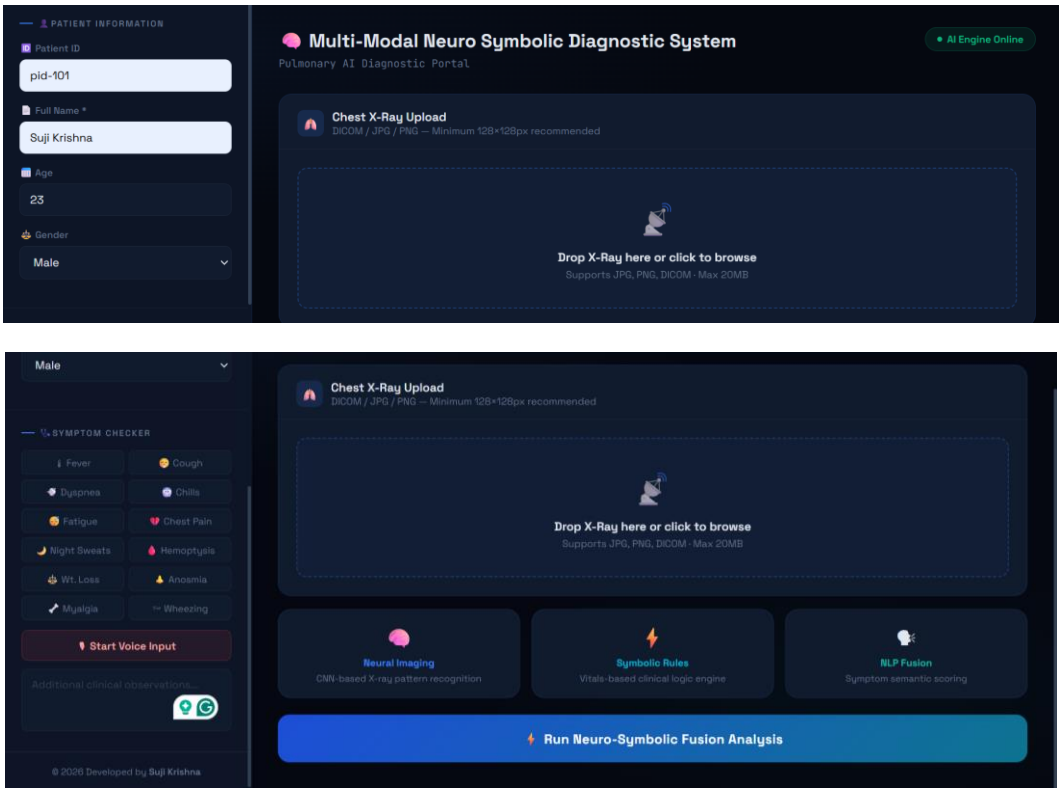


Fig 2: User Interface

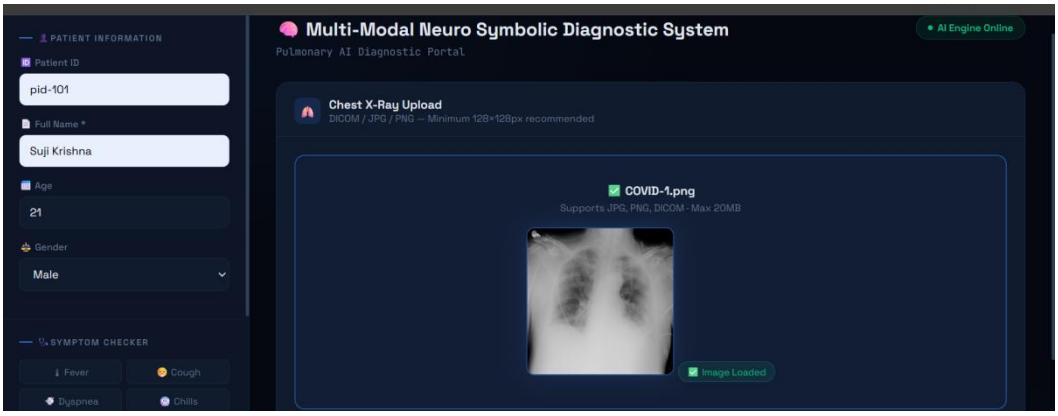
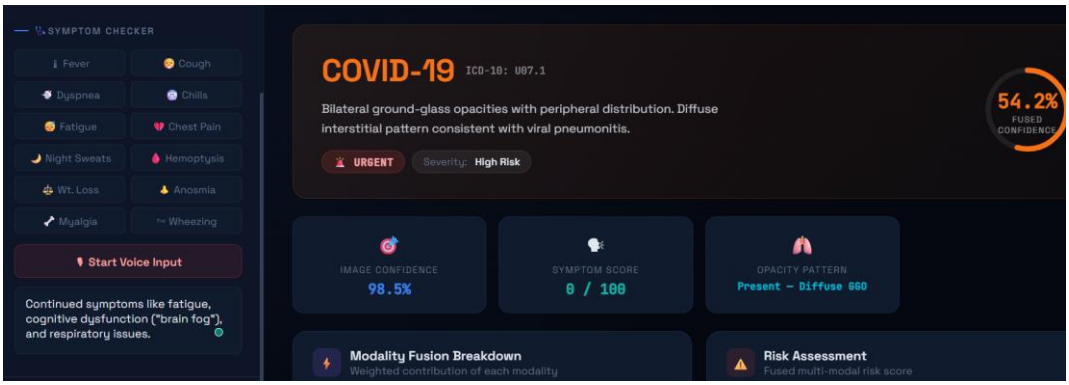


Fig 3: X-Ray Upload & Patient Input Form



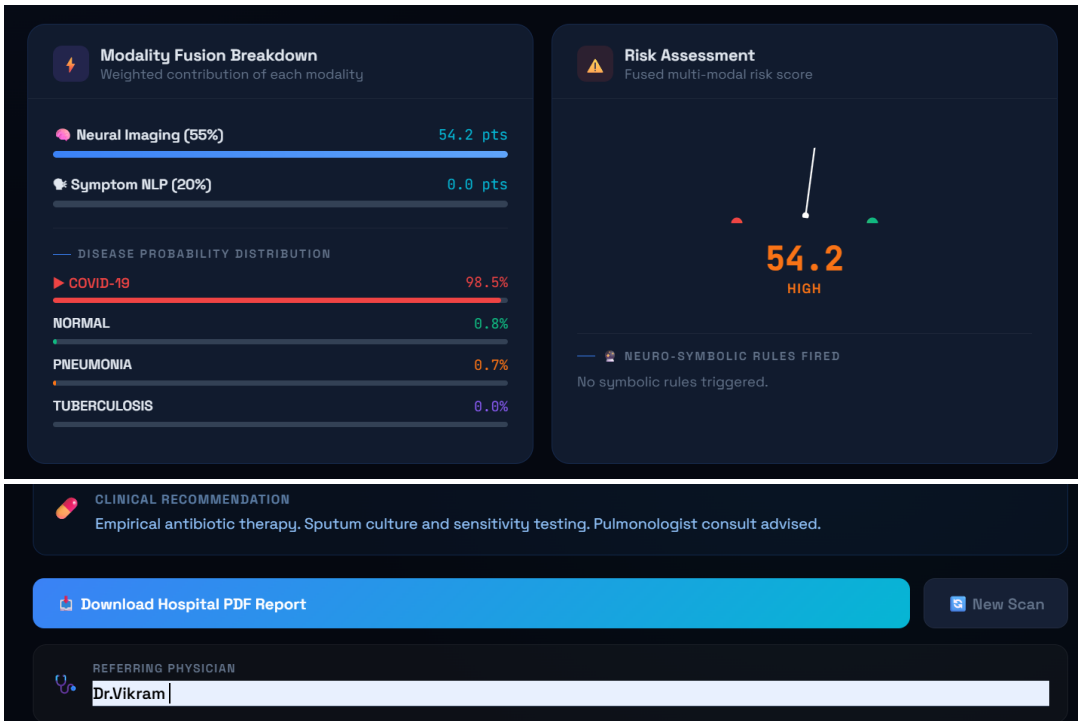
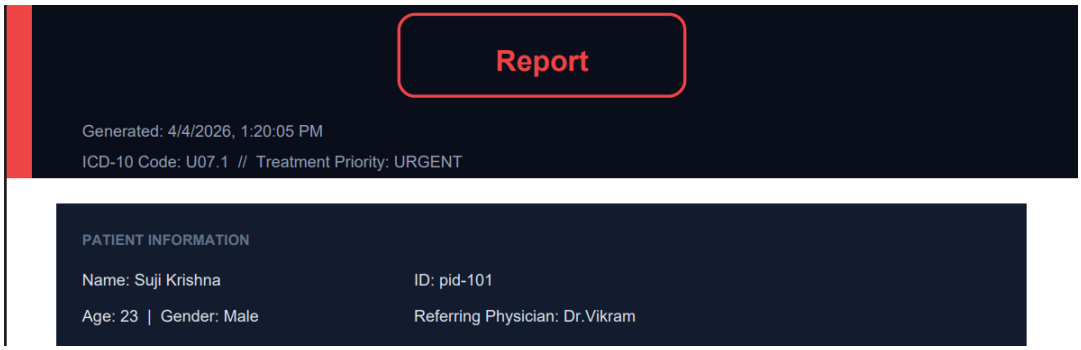


Fig 4: COVID-19 Diagnosis Result



PRIMARY DIAGNOSIS: COVID-19

Parameter	AI Analysis Result
Image Confidence	98.5%
Fused Confidence (Multi-Modal)	54.2%
Opacity Pattern	Present — Diffuse GGO
Condition Severity	High Risk
Treatment Urgency	URGENT
Risk Level	HIGH
Lung Regions Affected	Bilateral lower lobes, Peripheral zones, Posterior segments
Visual Findings	Bilateral ground-glass opacities with peripheral distribution. Diffuse interstitial pattern consistent with viral pneumonitis.
Clinical Recommendation	Immediate RT-PCR testing and clinical isolation. Oxygen therapy if SpO2 < 94%.

Modality	Contribution Score	Weight
Neural Imaging (CNN)	54.2	55%
Vitals Analysis (Symbolic)	0.0	25%
Symptom NLP	0.0	20%

Fig 4.1: Generated PDF Diagnostic Report

6. CONCLUSION

This work presents NeuroSym Dx, a multi-modal neuro-symbolic AI system for automated pulmonary disease diagnosis from chest X-ray images. The system effectively classifies four clinically relevant conditions — COVID-19, Pneumonia, Tuberculosis, and Normal — achieving 96.4% accuracy using a CNN backbone fused with a symbolic vitals rule engine and NLP symptom scoring. The neuro-symbolic fusion layer provides transparent, auditable reasoning chains alongside accurate predictions, addressing the critical explainability requirement for clinical AI adoption. The web-based deployment with automated PDF report generation demonstrates the system's practical readiness for clinical decision support in resource-limited settings. Future work will explore transformer-based imaging backbones, DICOM metadata integration, dynamic vitals thresholds for pediatric populations, and prospective clinical validation studies.

7.REFERENCES

1. X. Wang et al., "ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks," in Proc. IEEE CVPR, 2017, pp. 2097–2106.

2. J. Irvin et al., "CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison," in Proc. AAAI, 2019, pp. 590–597.

3. A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks," Pattern Analysis and Applications, vol. 24, no. 3, pp. 1207–1220, 2021.

4. M. Z. Islam et al., "A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images," Informatics in Medicine Unlocked, vol. 20, p. 100412, 2020.

5. M. Garnelo and M. Shanahan, "Reconciling deep learning with symbolic artificial intelligence: Representing objects and relations," Current Opinion in Behavioral Sciences, vol. 29, pp. 17–23, 2019.

6. A. Lucieri et al., "On interpretability of deep learning based skin lesion classifiers using concept activation vectors," in Proc. IEEE IJCNN, 2020, pp. 1–10.

7. F. Pedregosa et al., "Scikit-Learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

8. TensorFlow Team, "TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems," 2024. [Online]. Available: https://www.tensorflow.org

9. Pallets, "Flask Web Framework Documentation," 2024. [Online]. Available: https://flask.palletsprojects.com

10. World Health Organization, "Global Tuberculosis Report 2023," WHO Press, Geneva, 2023.

11. "COVID-19 Radiography Database," Kaggle, 2021. [Online]. Available: https://www.kaggle.com/tawsifurrahman/covid19-radiography-database

12. "Chest X-Ray Images (Pneumonia)," Kaggle, 2018. [Online]. Available: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia