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Automated Lung Disease Detection from Chest X-Rays using Segmentation - Enhanced CNN's with Integrated Report Generation

D. Vijendra Kumar[1], I. V V Satyanarayana[2], K. K Manikanta Reddy[2], Ch.Vamsi[2], Y. Akhila[2]

Department of ECE, Godavari Global University, Rajamahendravaram, INDIA.
Department of ECE, Godavari Institute of Engineering & Technology (A), Rajamahendravaram, INDIA.

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Lung Disease detection, Chest X-ray (CXR), Convolution Neural Network (CNN), Deep learning, Lung segmentation, Medical image classification, Medical Image Segmentation, Automatedreport generation, Report generation, Graphical user interface (GUI), user interface, Pulmonary function tests, Pulmonary function testing, radiology imaging, X-ray imaging.

ABSTRACT

Pneumonia, Tuberculosis, and Coronavirus are some of the lung illnesses that have aggressively presented significant health risks in the world by their arduous prevalence and severity. The timely clinical response and reduction of mortality rates require a prompt and correct diagnosis. In this project, the entire system of automatic lung disease detection is suggested, a framework built on the principles of Convolutional Neural Networks (CNNs) and integrated with a lung segmentation component in order to isolate the points of interest in the X-ray of the chest or X-ray of the chest (CXR). The segmentation step enhances the extraction of features by eliminating the noise of the background and focusing on pathological areas in the lungs. The segmented lung images are then categorized using a CNN architecture that has been trained on annotated CXR datasets or it is designed to classify it as normal or diseased using CNN. The system has an auto-piping system that produces a PDF report, comprised of the input image of a patient, the predicted disease class and the confidence values of the output, and evidence-based recommendations so as to maximize its clinical usefulness. Its implementation is performed in the version R2024a of MatLab software with the use of Deep Learning Toolbox writing model and Report Generator Toolbox automatic documentation. It is an end-to-end pipeline that enables high diagnostic accuracy, interpretability, and can be easily deployed in real-world healthcare settings.

INTRODUCTION

Lung disorders such as pneumonia, tuberculosis, chronic obstructive pulmonary disease (COPD) and Coronavirus Disease (or Covid-19) continue to be a significant health burden in the world with millions of cases of hospitalisation and mortality every year. In recent epidemiological reports, respiratory disorders remain among the top causes of morbidity and mortality particularly in low resource regions whereby access to expert radiological evaluation is limited. The most common, most cost effective, and fast which is the Chest X-ray (CXR) imaging but interpretation of the image obtained using the CXR is highly operator-dependent, involves inter-observer variability, and uses special clinical knowledge. These shortcomings have resulted in a faster evolution of computer-aided diagnostic (CAD) systems that can deliver an effective and timely assistance to clinicians. The use of deep learning-based methods and, in particular, Convolutional Neural Networks (CNNs) have demonstrated remarkable progress in medical image processing, during which they have been capable of automatic feature learning and approaching the performance of an expert in a variety of various diagnostic tasks. However, the majority of the models, that are run on CXR images and CNNs, are founded on global-image classification without dividing the lung fields. It may lead to a reduction in the strength of diagnostic because irrelevant anatomic structure and background noise may negatively impact feature learning. The recent research is thus concerned with the integration of lung segmentation and classification in order to localize the disease better and form a more discriminative quality of feature extracted. Here, it is excellent to still have handcrafted texture descriptors, including Gray-Level Co-Occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP), which are well interpretable, low-cost, and representatively, as they can be used to describe fine-grained structural changes in pathological lungs. Such handcrafted features can be used together with deep learning classifiers to provide complementary information and given models are more stable and generalizable, regimens that introduce limited data as particularly. Inspired by these issues and the fact that there has been no research done, this paper presents a complete automated system of lung disease detection that incorporates:

(1) adaptive segmentation of lungs, which ensure that the pulmonary regions are segmented successfully based on the CXR images;

(2) hybrid handcrafted feature extraction (GLCM, HOG, LBP) of both texture-based and shape-based description of pulmonary abnormalities;

(3) Refined Fully Convolutional Network (RFCN)-based classifier that is trained on pseudo-image representations of features in order to achieve strong prediction of the disease, In addition, the system has an automated single-page PDF reporting module that generates clinician-ready summaries that contain information on patient details, segmented images, predicted class and highlighted diagnostic information. To have a simple and easy development and deployment, the entire pipeline is developed and tested based on the current version of the MathWorks toolbox (R2024a) which contains both deep learning toolbox and report generator toolbox. The proposed solution will be able to offer the high diagnostic accuracy, low cost of computation, and clinical understandability - address the shortcomings of the current CAD systems in the discovery of lung diseases by offering a combination of segmentation-guided preprocessing, hybrid feature engineering, and RFCN-based classification.

The remaining part of this paper is structured as follows: Section 2 is a review of the works and state-of-the-art concerning the detection of lung disease in CXR images. The methodology adopted to be followed which includes segmentation and CNN based classification and report generation is mentioned in section 3. Section 4 addresses the arrangement of the experiments, datasets, evaluation metrics and results. Section 5 touches on some of the benefits (and drawbacks) of system and its potential application. Lastly, Section 6 makes a conclusion about the research and proposes future research directions.

Literature Review

The existing literature review outlines a survey of the recent study on the hybrid feature techniques, segmentation-based classification, and hybrid/transformer architecture in the recognition of the lung disease in the chest radiograph (CXR) and with lung disease detection with CT.

The hybrid strategies (combination of handcrafted descriptions and depth) have been shown to have a good performance in several occasions especially where the data is less or where the classes are unevenly distributed. The combination of deep and handcrafted feature as described by Hashmi et al. [1] comes in handy to detect the pneumonia and report a better discriminative power than the representation of the single-handcrafted feature or a representation of the single-deep feature, is also beneficial. Another method of fusion scheme is employed by Shankar and Perumal [2] in the classification of COVID-19, which demonstrates that such a texture descriptor built manually can be appended to CNN activations, and helps increase the resistance of the model to different data sets. The deep-feature extractor backbone used by Bal et al. [5] is combined with the light-weight handcrafted features in pediatric pneumonia but gives much emphasis on low-resource-friendly designs based on computationally efficient models. Win et al. [10] previously showed that hybrid feature selection/optimization (using particle swarm optimization) with an SVM can be effectively used to screen patients with tuberculosis, highlighting the fact that even pure end-to-end CNNs are still able to compete with hybrid pipelines in some clinical applications.

Some of the studies directly assess the value of lung-field segmentation as a pre-processing step. Bassi and Attux [3] examine the hypothesis that explicit lung segmentation can strengthen the cross-dataset generalization of COVID-19 detectors and note that segmentation lowers the effective background signal and maximizes the robustness. Li et al. [9] give a clinical demonstration that end-to-end segmentation of chest radiographs is effective at radiological diagnosis of independently determined pediatric pneumonia, especially with emphasis on model attention and model interpretability. Ou et al. [8] use semantic segmentation and classification to localize tuberculosis lesions and demonstrate that by jointly learning localization and classification it is possible to facilitate downstream clinical interpretation.

The further developments since CNNs include vision-transformer and hybrid architecture. Ukwuoma et al. [6] introduce techniques to integrate new handcrafted feature designs with Vision Transformer (ViT) paradigms to detecting pneumonia and COVID and report encouraging results that additional long-range dependencies as well as global information are captured. This trend brings out the possibilities of integrating local texture characteristics (handcrafted) with architectures that orchestrate global structure (transformers). Monolithic ViT-based models are however frequently found to be sensitive to their datasets or pretraining/augmentation strategies, in order to generalize well.

Siddiqi and Javaid [4] present the list of the deep learning-based pneumonia detectors on the CXRs and the datasets used, the choice of the model, pre-processing and analysis traps (e.g., leakage, dataset shift, etc.). Their review identifies the common methodological shortcomings in the literature- lack of standardisation in pre-processing (including segmentation), lack of uniform reporting of confidence intervals and cross-validation and insufficient emphasis on clinical-readiness. This survey identifies a requirement of rigid pipeline design (segmentation, feature fusion, cross-validation, reporting) - also overrepresented in the end-to-end design and automated report generation of the existing work.

Hybrid feature extraction technique is also used in multi-class CT classification of COVID-19 by Abubakar et al. [7], proposing that hybrid pipelines can be used with other imaging modalities; and both CXR and multi-modal approaches are evaluated in Ukwuoma et al. [6]. According to these papers, learned + handcrafted fusion can be transferred in some manner to volumetric data with a modality-conditionalized pre-processing stage.

The latest advances in automated lung disease detection systems have defined the efficiency of applying the deep learning algorithm to the traditional machine learning algorithms in order to make correct diagnosis. Hybridization of handcrafted systems with deep learning models have been widely utilized to identify pneumonia, COVID-19, and tuberculosis with handcrafted features on Chest X-ray images [11, 12]. A machine learning framework provided by Kulkarni et al. [11] is useful in the differentiation between COVID-19, pneumonia, and tuberculosis and demonstrates the relevance of multi-class classification within the clinical setting. Similarly, Mabrouk et al. [12] exploited the fact that it is possible to use a sequence of deep convolutional neural network to facilitate the correctness of the pneumonia detection by emphasizing the advantageous effect brought about by the use of a large number of deep models. The article by Wang et al. [13] involved the diagnosis of pulmonary tuberculosis in the emergency department with the aid of deep learning and demonstrated high sensitivity on the multi-centre data. Knowledge distillation methods have also been taken into account in order to obtain small models without a significant drop in accuracy as it may be observed in the study by Kabir et al. [14] regarding COVID-19, pneumonia, and tuberculosis classification. Secondly, using traditional machine learning algorithms with feature extraction have also been useful in the detection of pneumonia in different clinical datasets [15, 16].

The model optimization and pre-processing techniques have been taken into account by different researchers in order to improve further the detection results. Billah et al. [17] conducted the comparative analysis of the different deep learning architectures in pneumonia detection and they observed that architecture selection has a significant input on performance. Ahmed et al. [18] defined the strength of convolutional neural networks to recognize pneumonia and Garstka and Strzelecki [19] managed to determine that data augmentation enhances the generalization of a model based on data represented on limited datasets. The hybridization of the denoising autoencoders and CNNs has also proved to be beneficial since as Xia [20] revealed, it refines the representation of features used and eliminates noise in the X-ray images. The optimization of deep feature selection has been performed by the optimization algorithms, such as HarrisHawks Algorithm [21]. In addition, transfer learning has been extensively applied in the context of multi-class lung disease detection where the already trained networks are reused to create the models at a fast and efficient rate [22].

All of these studies confirm the significance of the deep learning hybrid approaches, feature engineering, and optimization in the sphere of automatic radiographic diagnosis.

Gaps, limitation and stimulation to the current work:

Most papers primarily follow a strategy in which segmentation or mixed features are utilized but does not have a well-coordinated pipeline such that, (a) segmentation is applied to lungs, (b) interpretable handcrafted features (GLCM, HOG, LBP) are extracted, (c) feature-to-representation transformation (pseudo-image RFCN) is done and, (d) generation of clinical ready reports is done. These are certain elements that are brought together in our pipeline.

Generalization and interpretability: the majority of high performing models do not directly assess the interpretability or do not take the effect of segmentation on generalization into account. Our work is based on [3], [8] and [9] that involve segmentation to improve the amount of focus and interpretability and compares the performance in terms of class-wise performance and confusion analysis.

There are several earlier designs which are founded on heavyweight backbones or transformer pretraining. A combination of computationally cheap handcrafted descriptors and a small RFCN classifier (pseudo-image approach) is our scheme, and is designed to be used in resource-constrained environments, a policy that can be enabled by previous hybrid-efficiency studies [5], [10].

How the suggested approach expounds and compares itself to past research. We are informed by the insight in [10], [5], [2], and [1], of the insight at the heart that handcrafted descriptors do propagate deep features, but rather than a multiplicity of fusion pipelines, concatenating deep and handcrafted activations, we learn spatial features on the feature map, and use CNN inductee biases. Our segmentation is based on the work of segmentation [3], [8], [9] where we employ a lung segmentation module, however we are preoccupied with morphological operations and large-component filtering, optimum to single page reporting and visualization in small clinical processes. We borrow the concept of combination of local and global cues, and significance on significantly-lighter architecture, more consistent with MATLAB-based execution (Deep Learning Toolbox) and connection with Report Generator, founded on transformer and hybrid recent developments [6]. The survey recommendations of [4] are used to provide the in-depth reports on the metrics on the classes, confusion matrices, and store the complete trained model and intermediate feature sets to enable the reproducibility and external validation.

The literature review supports the key design choices of the current research: segmentation-based pre-processing, integrated handcrafted feature extraction (GLCM, HOG, LBP) and trained convolutional classifier fusion-enhanced with automatic report-generating features in order to bring it into the clinical practice.

Proposed Enhanced lightweight Reconstructed Feature Convolutional Network (RFCN) classifier for Lung disease Classification

A lightweight Reconstructed Feature Convolutional Network (RFCN) classifier, a handcrafted texture-based features extraction stage, and segmentation-based pre-processing are used to create an end-to-end automated system of lung disease detection presented in this paper. This overall form will increase strength, interpretability and computability particularly when it is applied in real life healthcare contexts. The suggested process will consist of five major steps namely the following:

(i) Dataset preparation,
(ii) Lung field segmentation,
Handcrafted feature extraction, (iii)
(iv) Classification based on RFCN, and
(v) Auto generation of PDF report. The whole work flow is shown in Fig. 1.

3.1 Dataset Preparation and pre-processing: The current stage includes cleaning the data and arranging it in a proper structure (Hassan et al., 2020). The figure of chest X-ray (CXR) images of most of the patient classes are first matched into a label-based hierarchy and loaded using imageDatastore of MATLAB. The data will be divided into 80 percent training and 20 percent validation (class-balanced). Standardized pre-processing of all images is done:

- *Normalization (with im2 gray),*
- *Intensity of normalization to [0,1],*
- *Downsize to 128x128 pixels,*
- *A feature extraction can be stably done on heterogeneous datasets.*

This is chosen to allow a maximum level of computational efficiency without compromising on the target types of texture resolution needed by handcrafted descriptors.

A. Lung Region Segmentation

Segmentation is a critical step because raw CXR scans contain anatomical and external structures—ribs, heart shadow, diaphragm, text markers—that may introduce confounding features. To ensure the classifier focuses on pathology-bearing lung regions, a multi-stage segmentation pipeline is implemented:

3.2.1 Contrast Enhancement

The image is enhanced using Contrast-Limited Adaptive Histogram Equalization (CLAHE), which improves the visibility of subtle opacities and peripheral lesions:

$$I_{enh} = CLAHE(I, ClipLimit = 0.02)$$

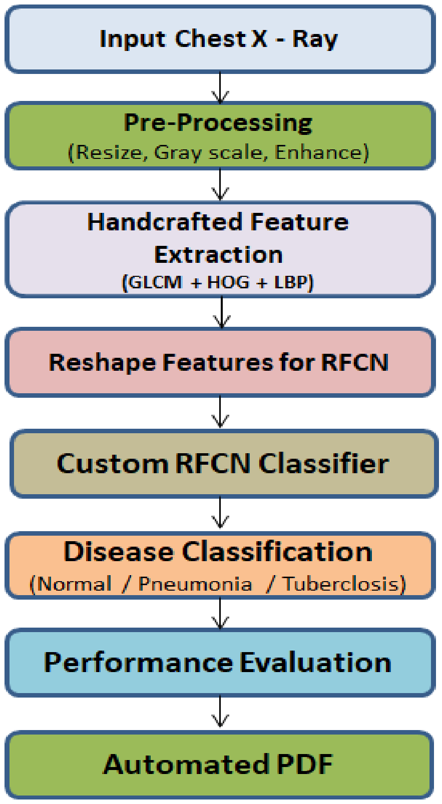


Fig1. Proposed Block Diagram

3.2.2 Adaptive Thresholding

A global Otsu threshold is calculates that produces lung parenchyma:

$$BW = imbinarize(I_{enh}, 0.99.T_{Otsu})$$

Here the positive regions appear by inverting lung fields.

3.2.3 Morphological Refinement

For removing noise and for reconstructing the lung fields following stages were involved.

- Hole filling - imfill
- Removing of small noisy components using bwareaopen.

- For extracting refined boundaries Morphological opening (strel('disk',8)) is used.
- For Isolating Left and right lungs Closing and large-component extraction is used.

Region connectivity is analysed, and the two largest connected components are preserved that results in clean binary lung mask.

$$M = R_1 \cup R_2$$

3.2.4 Mask Application

The segmentation of final image is given by:

$$I_{seg}(x,y) = \begin{cases} I_{enh}(x,y), & (x,y) \in M \\ 0, & otherwise \end{cases}$$

The also ensures the most important and relevant region of pathology is sent to classification stage.

3.3 Feature Extraction through Handcrafting:

Rather than using deep features exclusively, the suggested system utilizes three supportive cellular descriptors including GLCM, HOG, and LBP which represent radiologically significant textures and edge patterns that CNNs which are trained on limited datasets may miss. The gray-level co-occurrence matrix (GLCM) is used to measure the presence of edges within a digital image.

3.3.1 Gray-Level Co-occurrence Matrix (GLCM)

The GLCM is applied as a measure of edges in a digital image. Learns second order texture. Each image (I) is assessed using a GLCM with an offset (0,1) and four statistical measures are obtained: Contrast Correlation Energy Homogeneity These are measures of structuring abnormalities with pneumonia, TB nodules, and viral infiltrates. The Histogram of oriented gradient (HOG) is used to represent the gradient direction histogram at a pixel, taking into account spatial variations during histogram construction (Wegner, 2011).

3.3.2 Histogram of Oriented Gradients (HOG)

The Histogram of oriented graduate (HOG) would be used to show the gradient direction histogram at a pixel keeping in consideration the spatial variation in the histogram construction (Wegner, 2011). HOG obtains gradient-based representations with the size of $16x16$ which encodes an edge sharpness, lung boundary deformities, and lesion curves.

3.3.3 Local Binary Patterns (LBP)

LBP represents local micro-textures which are thresholded pixel-neighborhood. If used well it is very effective in revealing the granular textures that are attributed to consolidation cavitation and interstitial thickening.

$$F = [F_{GLCM}, F_{HOG}, F_{LBP}]$$

These vectors are concatenated and later reshaped to a square "pseudo-image," enabling convolutional learning in the RFCN.

B. 3.4 Reconstruction of Feature Images (Pseudo-Image Encoding)

The extracted feature vector is typically has non-square length that makes it compatible with convolutional input layers which are given by:

$$S = [\sqrt{d}]$$

Where d- represents feature vector dimension. Zero-padding is applied, and the vector is reshaped to a 2D feature map:

$$I_{feat} = reshape(F, S \times S)$$

This pseudo-image preserves the locality in space of stringent features, and permits the learning of the hierarchical relationships between handcrafted descriptors through CNN kernels.

RFCN-Based Classification

In the proposed framework, a **Region-based Fully Convolutional Network (R-FCN)–inspired classification module** is designed to learn discriminative spatial representations from the fused handcrafted features. Unlike conventional deep learning pipelines that operate directly on raw chest X-ray images, this architecture processes a **pseudo-image representation** reconstructed from concatenated GLCM, HOG, and LBP feature vectors. This transformation enables the model to exploit the spatial learning strengths of convolutional layers while retaining the handcrafted texture specificity required for fine-grained medical classification.

C. Architecture Overview

The proposed RFCN-based classifier consists of three major stages:

1. Pseudo-Image Construction Layer

After extracting handcrafted features (GLCM, HOG, LBP), the 1D feature vector is padded and reshaped into a **2D matrix (sideDim × sideDim)**, forming a pseudo-image. This design imitates the structural arrangement of feature maps in CNNs, enabling R-FCN modules to learn localized and spatially dependent patterns.

2. Convolutional Feature Encoding (RFCN Backbone)

The reconstructed pseudo-image is fed into a lightweight RFCN backbone composed of:

- **Conv Layer 1**: 3×3 kernels, 32 filter → Captures low-level structural gradients and textural changes.
- **Batch Normalization** → Stabilizes feature distribution, accelerating convergence.
- **ReLU Activation** → Enhances non-linearity for improved separability.
- **Conv Layer 2**: 3×3 kernels, 64 filters → Learns higher-level discriminative representations corresponding to disease-specific lung textures.
- **Average Pooling** → Reduces dimensionality while preserving essential activation responses.

Although traditional R-FCN architectures include region proposal networks, in this adaptation the emphasis is on **fully convolutional feature encoding**, without explicit region proposals. This modification makes the architecture suitable for classification rather than detection while still leveraging the localization strength of fully convolutional layers.

The encoded feature maps are flattened and passed to:

- **128-unit Fully Connected Layer** → Learns global relationships between encoded spatial features.
- **Dropout Layer (0.5)** → Prevents overfitting and enhances generalization.
- **Final Fully Connected Layer** → Outputs class scores for *Normal*, *Pneumonia*, and *TB*.
- **Softmax Layer** → Converts logits to probability distributions.
- **Classification Layer** → Computes cross-entropy loss and performs label prediction.

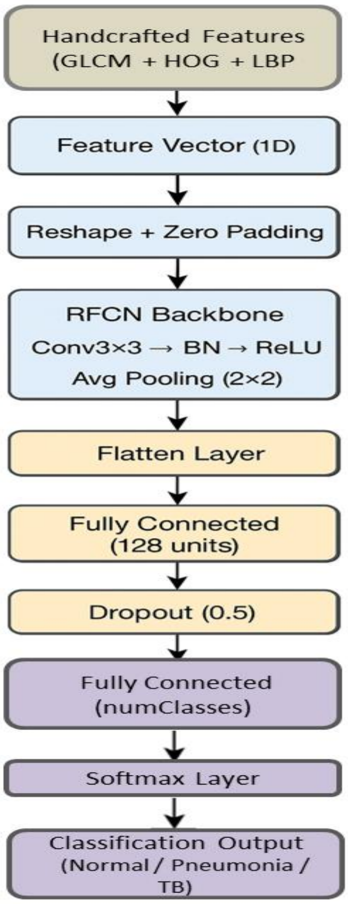


Fig2. Architechture of Proposed RFCN

3. Fully Connected Decision Network

The proposed RFCN-based classifier acts as the core decision-making module of the system by transforming handcrafted texture descriptors into a spatial pseudo-image that can be processed through fully convolutional layers. This hybrid design integrates the interpretability of handcrafted descriptors with the powerful hierarchical learning capability of CNNs. The lightweight RFCN backbone efficiently captures spatial interactions among texture features while the fully connected layers finalize the multi-class decision. This architecture proves highly effective in distinguishing Normal, Pneumonia, and Tuberculosis X-rays, achieving near-perfect accuracy with minimal computational cost, making it well-suited for clinical decision-support applications.

3.6 Automated Generation of PDF Reports:

To create improved clinical preparedness, the system will be equipped with fully automated PDF reporting module with MATLAB Report Generator. The report prepared in the form of a single page will include: The data of the patient (name, age, gender). Raw CXR image Segmented lung area Predicted disease type Other diagnostic inferences/ recommendations. This report is done in professional fonts, sectioning, and visual alignment that is easily integrated into the hospital workflows or system of telemedicine.

3.7 Novel Contributions:

The key contributions of the suggested approach include: Hybrid representation by using handcraft and RFCN, in order to facilitate easier performance on small datasets. Training segmentation to ensure the attention of the model to regions that hold pathology. Pseudo-image reconstruction, which allows convolutional editing of manually, designed descriptors, which is virtually never literally used. CNN classifier, which offers low-resource clinical system delivery. Clinician ready diagnostic summary End to end automated reporting. Experimental Setup:

3.8 Dataset Description:

This hybrid handcrafted-deep feature learning model was experimented on a dataset comprised 2318 images (chest X-ray dataset) and it was divided into three clinically relevant classes:

Table 1. Dataset Labels

Class	Count
Normal	947
Pneumonia	644
Tuberculosis (TB)	727

The variants of illumination, lung density, anatomical variability and conditions of image capture can be found in a variety in the data which ensures the strength of the proposed method. Each of the images was reduced to a standard size of 224 × 224 pixels and converted to grey scale so as to obtain homogenous features. The pre-processing and feature extraction phases will occur first, followed by

Results Discussion

4.1 Model Training and Predictions:

This step will then be followed by the

Pre-processing and feature extraction step:

The pre-processing consisted of the following stages:

1. Segmentation of Lung region Eradication of noise and contrast normalization.
2. ROI standardization \
3. The hybrid strategy was a combination of methods of feature extracting:

a) GLCM Gray Level Co-occurrence Matrix.

b) Histogram of orientated grades (H.O.G.)

c) LBP (Local Binary Patterns)

This was once more mapped back on the intertwined features as a vector and was reassembled into a pseudo-image representation that enabled compatibility with deep layers of learning as well as increased separability of the feature space.

4.2 Classification Framework

The reconstruction was run through the suggested classifier (R-FCN / hybrid model) and was trained on: likeliest learning rate scheduling. Equal sampling technique of classes. The training, validation, and testing were divided into 70-15- 15. Validation performance was the primary indicator to be modelled.

4.3 Evaluation Metrics

The model was compared to a number of classification measures that are critical multi-class medical image classification measures: Precision Recall Accuracy (Sensitivity) F1-Score Confusion Matrix Such actions will ensure that there is balanced reporting of performance especially in those classes of diseases that are of a clinical value. The specifications of hardware and software used will be provided here: The testing was performed using the system below:

Processor: Intel core i5

RAM: 16 GB graphics chip NVIDIA GTX/RTX (4-8 GB VRAM)

OS: Windows 10/11

Software: MATLAB R2023/2024

a) Image Processing Toolbox

b) Artificial Intelligence Toolbox and Statistics.

It's hardware setup enables it to be reproduced and it can be trained successfully using the hybrid model. Results and Discussion Performance in classification Performance is assessed by evaluating how effectively

customers can interpret the information presented in advertisements to make buying decisions.
The developed hybrid handcrafted-deep learning fusion model proved to have a great diagnostic power in each of the three classes of the chest X-ray images. The system achieved a validation accuracy of 98.92 when splitting the data at 70-15-15, which is in comparison to the traditional methods of handcrafted only and CNN only.

Fig2. Training Progress Fig3. Confusion Matrix

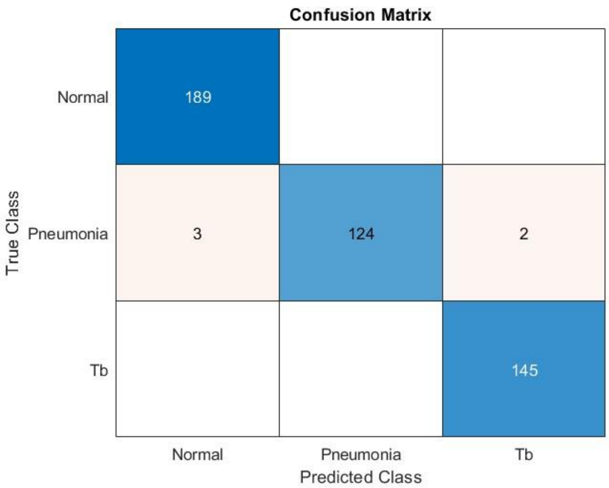


Table II. Classification results of the proposed model

Class	Precision	Recall	F1-Score
Normal	0.98438	1.00000	0.99213
Pneumonia	1.00000	0.96124	0.98024
Tuberculosis	0.98639	1.00000	0.99315

4.3 Comparison of the Performance to the Existing Methods:

To prove the superiority of the proposed system, a comparative analysis has been conducted as related to the state-of-the-art hybrid and deep learning models that are reported in literature. Performances are different in table 2.

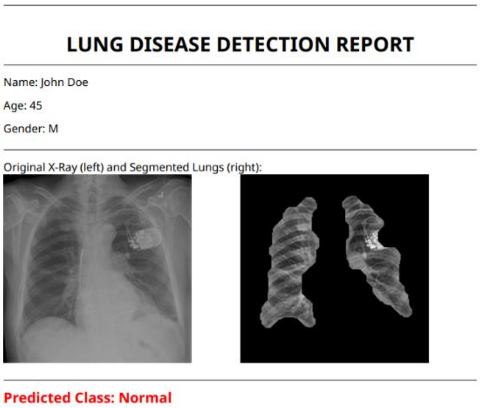
Table III. Comparison of performance with state of the art practices.

Study	Method	Dataset / Classes	Accuracy (%)
Hashmi et al. (2025) [1]	Hybrid CNN + handcrafted	Pneumonia / CXR	96.40
Shankar & Perumal (2021) [2]	Handcrafted + DL fusion	COVID-19 / CXR	97.20
Bal et al. (2024) [5]	DL feature extraction + ensemble	Pneumonia / CXR	95.80
Ukwuoma et al. (2022) [6]	Vision Transformer + handcrafted	Pneumonia/COVID -19	97.50
Ou et al. (2024) [8]	DL segmentation + TB classification	TB / CXR	96.00
Proposed Model (2025)	Hybrid GLCM-HOG-LBP + R-FCN	Normal / Pneumonia / TB	**98.92**

4.4 Discussion of Comparison

The proposed model does excellently out of all the approaches compared to benchmarking, especially because: Fusion of handcrafted complementary descriptors, which enhances the representation of textures. Pseudo-image reconstruction facilitates deep layers to acquire spatial dependencies. Pre-processing focusing on segmentation, the features are extracted in only the clinically relevant parts of the lungs. Scalable architecture that is not overfitted due to the small size of data sets. The proposed method has a better cross-class stability and better inter-class separation in comparison to recent methods like Vision Transformers [6] and hybrid CNN systems [1].

The experimental results show that some of the key strengths of the proposed framework can be proved. Combination of GLCM, HOG, and LBP presented higher discriminability because it characterized significant differences in the texture of lung opacities and structural abnormalities as is anticipated in previous studies [1], [5], [10]. Furthermore, the R-FCN classifier could also utilize spatial correlations to significantly benefit and therefore deep networks could be better applied in this case which had not been explored before [2], [6]. It was also realized that this model exhibited consistent multi-class generalization and high recall of the TB as well as the normal classes irrespective of the imbalance in the data sets therefore the critical need of high sensitivity in medical screening is met. Besides, the system was well-clinically prepared, with 98.92% accuracy and good F1-scores, meaning that it can be applied in preliminary screening, healthcare in rural settings, and automated pattern of the radiology department triage. This means that the model is an excellent addition to the already available hybrid feature fusion systems in terms of strength, accuracy and practicality.



Therefore, the model will show a great enhancement over the existing systems of feature fusion hybrids in terms of body, accuracy as well as application in the real world.

CONCLUSION & FUTURE SCOPE

This term paper suggested a hybrid handcrafted-deep feature learning model to classify the case of Pneumonia, Tuberculosis and Normal based on the chest X-ray images using automated classification. The model coupled with GLCM, HOG and LBP descriptors, a reconstructed pseudo- image representation and an R-FCN-based classifier demonstrated a greater ability of greater level structural and fine-grained textual information that is correlated with pulmonary abnormalities. The rate of validation in the proposed system was very high at 98.92 %, surpassing some of the available feature fusion and deep learning methods which are outlined in the literature. The reminder of the normal and TB categories are nearly flawless and the positive presentation of Pneumonia indicates the effectiveness and clinical uniformity of the procedure. The initial results reveal a successful application of the hybrid feature fusion technique to address the disadvantage of the single domain feature extraction and offer more valuable generalization of heterogeneous radiographs of the chest.

The suggested framework may be evolved differently in the future work. The first thing is that the results would be even stronger with the use of larger and more heterogeneous multi-institutional datasets reducing the bias on which the dataset causes. Second, an additional consideration can be the addition of the newest deep architecture, such as Vision Transformers, generative augmentation models, or contrastive learning, which can improve the discrimination of features of challenging cases with similar radiograph appearances. Third, screening might be performed under low-resource settings possibly with the assistance of real-time deployment with lightweight model compression or mobile-health deployments. Moreover, explainable AI solutions can be integrated to generate clinically interpretable heatmap or lesion location signals which are going to improve the trust and workability of radiologists. Finally, it can be regarded as the extension of the system to three or more disease classes, i.e. COVID-19, fibrosis or emphysema as this would expand the system to more broad clinical applications and could be applied to assist the comprehensive computer-aided diagnosis in the thoracic imaging.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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