RESEARCH ARTICLE

Lungs Disease Detection Using Deep Learing

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Abstract

Lung diseases such as COVID-19, pneumonia, and tuberculosis remain major public health challenges worldwide, emphasizing the urgent demand for accurate and efficient diagnostic methods. This research explores the use of a Convolutional Neural Network (CNN)-based framework for binary classification of chest X-ray images to detect abnormalities. The methodology incorporates preprocessing techniques such as image resizing, normalization, data augmentation, and grayscale transformation to improve input data quality. CNN architecture comprising convolutional, pooling, fully connected, and dropout layers were trained and evaluated on publicly available datasets. The model attained a test accuracy of 92%; nevertheless, performance metrics revealed a disparity between the two classified categories. Class 0 (Normal) had precision (83%) and recall (90%), resulting in an F1-score of 0.80, whereas Class 1 (Abnormal) demonstrated higher precision (88%) and recall (90%) with an F1-score of 0.88. This highlights the need for further optimization to enhance the detection of normal cases. The findings underscore the potential of CNNs in automating lung disease detection but also reveal areas for improvement in model robustness and class balance.

Keywords: convolutional neural network, coronavirus disease of 2019, pneumonia, tuberculosis, medical imaging.

1 Introduction

Lung disease is a general term used to describe a wide range of conditions that impact the lungs and the respiratory system, significantly impacting global health. These disorders include chronic obstructive pulmonary disease (COPD), asthma, pneumonia, COVID-19 and tuberculosis (TB), both of which may arise from a range of different causes, such as infections, environmental pollutants, genetic predispositions, and lifestyle choices like smoking. According to the World Health Organization (WHO), respiratory illnesses constitute one of the primary causes of global mortality, impacting millions of people annually [1]. For instance, pneumonia alone causes approximately 2.5 million deaths each year, especially affecting children under five and older adults. Tuberculosis remains a major health concern, with over 10 million new cases recorded each year. The COVID-19 pandemic has underscored the significant global burden posed by lung diseases, with millions of cases and substantial mortality rates reported worldwide. Effective management and early detection of these conditions are critical to improving patient outcomes and reducing healthcare burdens. However, developments in medical technology, particularly involving deep learning and Artificial intelligence presents promising solutions to improve the diagnosis

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and treatment of lung diseases, with the potential to transform healthcare practices and outcomes on a worldwide.

Traditionally, Lung disease diagnosis primarily relies on conventional methods, including physical evaluations, reviews of medical history, and laboratory investigations. Physicians often use stethoscopes to listen to abnormal lung sounds; Patients might have sputum or blood tests performed to identify infections or indicators of inflammation. Chest X-rays and computed tomography (CT) scans are utilized to assess and visualize abnormalities in the lungs structure. While these methods are foundational, they have notable drawbacks. Sputum tests and physical examinations may not be as sensitive or specific as they may be, leading to incorrect diagnoses [2]. Additionally, the interpretation of X-rays and CT scans is reliant on the radiologist's specialized knowledge, with manual evaluation often being both time-consuming and vulnerable to human inaccuracies.

Advancements in imaging technology have enhanced the ability to diagnose respiratory disorders by providing comprehensive visualization of lung anatomy through chest X-rays and CT scans [3], allowing for the detection of anomalies such as fluid accumulation, infections, and tumors. These images are frequently put through to machine learning techniques to improve diagnostic accuracy. Conventional machine learning techniques typically include steps such as feature extraction followed by classification, such as Support Vector Machines (SVM) and Random Forests, which are trained on labeled image datasets to Detect disease-specific patterns in lung-related disorders. While these methods Having increased the effectiveness of diagnosis, they still rely on the quality of the complex patterns may not be fully represented by the features that were extracted, present in image-based data.

Deep learning has advanced lung disease diagnosis by using neural networks to automate both feature extraction and classification processes. Convolutional Neural Networks (CNNs) have demonstrated strong performance in interpreting chest X-rays and CT scan images, The high precision in recognizing a variety of lung diseases, such as COVID-19, pneumonia, and tuberculosis, is made possible by directly learning hierarchical features from raw image data, which eliminates the requirement for human feature engineering. Deep learning frameworks are used by sophisticated architectures like Efficient Net and Dense Net to enhance model generalization and diagnostic accuracy [4]. Several studies have indicated that deep learning models can exceed the performance of traditional methods by offering greater precision and reliability, which plays a crucial role in early detection and improving treatment outcomes.

Convolutional Neural Networks are extremely effective tools for classifying images since they can automatically recognize and extract characteristics from raw image data, reducing the need for manual feature engineering. Prominent models like VGGNet and ResNet are commonly used for these tasks. VGGNet, developed by Simonyan and Zisserman in 2014, is one such example, VGGNet is a deep convolutional neural network architecture known for its straightforward design and effectiveness. It utilizes a series of convolutional layers with 3x3 filters and max-pooling layers, enabling it to capture detailed information through images. By using labelled datasets of chest X-rays for training, the model has been modified for the diagnosis of lung diseases. to distinguish between different diseases such as pneumonia, tuberculosis, and COVID-19 [5]. VGGNet's straightforward architecture and pre-trained weights make it relatively easy to fine-tune for specific tasks, enhancing its utility in medical image classification, as demonstrated in widely cited studies.

ResNet (Residual Networks), introduced in a prominent architecture, brings the concept of residual learning to mitigate the vanishing gradient issue, facilitating the training of much deeper neural networks [6]. This model's ability to learn residuals or differences between layers helps in improving classification accuracy. ResNet has been effectively used for detection of lung disease by using its deep design to find complicated patterns in X-ray images. Its robustness and high performance on various benchmarks make it a valuable model for medical image classification. The benefits of using CNN-based models like VGGNet and ResNet in recent years include their exceptional accuracy, their ability to handle big datasets efficiently, and their suitability for identifying a variety of lung conditions. By automating the processes of feature extraction and classification, these models provide significant benefits over traditional methods, resulting in prompt and efficient diagnostic assistance.

2 Related Work

Respiratory disorders, commonly known as lung diseases, encompass a range of conditions that affect the airways and lung tissues [1, 2]. Deep learning techniques are essential for determining and classifying these diseases within medical imaging [2]. Conditions like pneumonia, tuberculosis, COVID-19, and lung cancer can be detected through X-ray and CT scans using deep learning models, including methods to learning such as Sequential, Functional, and Transfer [3], which have a significant worldwide influence. The Forum of International Respiratory Societies claims that [4], millions of people suffer from conditions like asthma, tuberculosis claims 1.4 million lives annually, lung cancer causes 1.6 million deaths, and pneumonia is responsible for millions of fatalities. The COVID-19 The pandemic intensified this problem, affecting millions and placing immense strain on healthcare systems across the globe [5]. Consequently, lung diseases have become a major contributor to mortality and long-term disability. Early detection is crucial for improving recovery chances and enhancing long-term survival rates [6, 7]. Traditionally, lung diseases are diagnosed using methods such as skin tests, blood tests, sputum sample analysis [8], chest X-rays, and computed tomography (CT) scans [9]. Recent advancements have shown that deep learning, when applied to medical images, holds great promise for detecting lung diseases. In this proposed model, trained on open-source datasets, achieved high accuracy, notably a Sequential model with an F1 score of 98.55% for pneumonia and 97.99% for TB, and a 99.9% accurate functional model for lung cancer, outperforming existing methods in efficiency and computational cost [3].

Several techniques for deep learning, such as Convolutional Neural Networks, Visual Geometry Group (VGG)-based networks, and Capsule Networks, have been employed for lung disease prediction; however, CNNs often face challenges related to image orientation. To address this issue, Chen et al. [10] proposed VDSNet, a hybrid model that combines the VGG architecture, data augmentation techniques, and spatial transformer networks within a CNN framework. The model was developed using Jupyter Notebook, TensorFlow, and Keras, and tested on the NIH chest X-ray dataset available on Kaggle. VDSNet demonstrated superior demonstrated superior performance relative to other models, attaining a validation accuracy of 73%. This framework offers a streamlined solution for lung disease detection, aiding medical professionals [11].

The number and variety of chest X-ray (CXR) datasets have increased rapidly over the past ten years, and deep learning techniques have advanced significantly as well. This review compiles insights from over 200 recent studies. (2018–2023) that analyze CXR Imaging used to recognize and differentiate lung disorders using deep learning and other advanced machine learning techniques. It classifies these studies according to the methodologies employed and the targeted diseases, while also assessing existing challenges and proposing directions for future research. The results highlight the critical need for further technological advancements to enhance patient outcomes by demonstrating how deep learning can significantly improve diagnostic speed and accuracy [10].

Creswell et al. [12] proposed the three approaches for tuberculosis Detection is performed using CNN-trained models. In the first method, CNNs can be used to extract features, and then an SVM classifier is employed for training. The second technique uses an SVM classifier to train features that are extracted from coreference resolution (CR). The third technique creates an ensemble of classifiers by combining the two earlier methods. They examined these techniques using 139 X-ray images from Montgomery 662 from the Shenzhen dataset and the dataset. Although these models speed up processing, their insufficient accuracy renders them unsuitable for reliable medical diagnosis. Davenport et al. [13] proposed extracting both local and global characteristics from radiographs using the deep neural network model Mask RCNN and highlight infected regions with heat maps. Despite these advantages, their ensemble of the models ResNet50 and ResNet101 provided less precise outcomes than anticipated and demanded considerable GPU computational resources for training. Jiang et al. [14] proposed four models, including CNN and LSTM-CNN from scratch and pretrained ResNet152v2 and MobileNetV2, to diagnose pneumonia from chest X-rays. Despite their diagnostic capabilities, these models have a large design that requires a lot of processing and computing resources because they have hundreds of millions of trainable parameters [15, 16].

Lung disease diagnosis capabilities have been greatly enhanced over the last ten years by deep learning advancements and easier access to chest X-ray (CXR) datasets [17, 18]. More than 200 recent papers

(2018–2023) are reviewed in this study focused on classifying CXR images according to diagnostic methods and specific diseases using machine learning techniques [19]. Given the severe effects of COVID-19 on the respiratory system, early detection is critical. Notably, a hybrid approach combining traditional CNNs with quantum classifiers achieved training and testing accuracies of 98.9% and 98.1%, respectively, on the Coronavirus Radiography Dataset. The model uses custom CNN for feature extraction and two novel quantum classifiers Multi-Multi-Single (MMS) and Multi-Single-Multi-Single (MSMS) outperforming standard deep learning models and validated on the IBM Q-QASM quantum computer [20]. The purpose is to enhance the reliability, efficiency, and accessibility of diagnosing lung diseases [19].

This study presents a multichannel deep learning method for detecting lung diseases from chest X-ray images by combining features extracted from EfficientNetB0, B1, and B2 models. These features are then processed through non-linear layers and a stacked ensemble classifier, resulting in accuracies of 98% for pediatric pneumonia, 99% for tuberculosis, and 98% for COVID-19, demonstrating the approach's effectiveness and reliability for point-of-care diagnosis [20]. Furthermore, this paper presents a novel framework for differentiating pneumonia from COVID-19 using chest X-ray images. The methodology encompasses dataset acquisition, image enhancement, refined ROI extraction, feature extraction, utilizing median filtering, histogram equalization, and dynamic region growing. However, Classification is carried out using multiple techniques, including deep learning with RNN and LSTM, demonstrating superior accuracy compared to current methods.

Various deep learning techniques [17] have been employed to develop a model for the detection and classification of lung nodules using computed tomography (CT) scans. To ensure accurate classification of lung nodules as benign or malignant and to avoid delays in diagnosis, the highest level of precision was required. When compared to other methods, the deep learning approaches used for lung nodule classification produced promising results. The deep learning architecture significantly enhanced the classification system's accuracy when mutations were incorporated. This approach was applied to detect early-stage malignant lesions and to establish new insights into nodule categorization [18].

Lung cancer continues to be a leading cause of cancer-related mortality worldwide, with early detection playing a vital role in improving survival rates [22]. However, traditional diagnostic approaches such as CT scans and blood tests are often labor-intensive and time-consuming. To address these limitations, several advanced deep learning models have been proposed. Lung-Retina Net, a Retina Net-based architecture, incorporates multi-scale feature fusion and a lightweight context module, achieving 99.8% accuracy and demonstrating strong performance in early tumor detection [9]. Another approach leverages a transformer-enhanced framework with adaptive anchor-free mechanisms and an improved feature pyramid network, using a dataset of 1,608 labeled CT images to achieve a mean average precision (mAP) of 96.26%, surpassing YOLOv9 and YOLOv10 [21]. Additionally, a lightweight hybrid model combining CNNs and Vision Transformers with Inception Next achieves up to 99.54% accuracy, offering efficient and precise classification of lung cancer subtypes, and significantly advancing early detection and clinical outcomes [4].

3 Methodology

The approach employed designing and assessed the CNN model for Detection of Pneumonia and other abnormalities through binary classification of chest X-ray images as shown in Figure 1.

3.1 Dataset Preparation

The dataset utilized consists of chest X-ray images organized into three distinct subsets:

- **Training Set:** implemented for model training.
- **Validation Set:** used for evaluating the model's performance throughout training and modifying hyperparameters to avoid overfitting.
- **Test Set:** Implemented to analyze the performance of the final model.

Each subset is divided into two classes, representing normal and abnormal conditions (e.g., "NORMAL" and "PNEUMONIA"). The dataset is structured into directories, and images are pre-classified according to these labels.

3.2 Preprocessing

Data preprocessing was applied to adjust the images for CNN input:

1. **Image Resizing:**

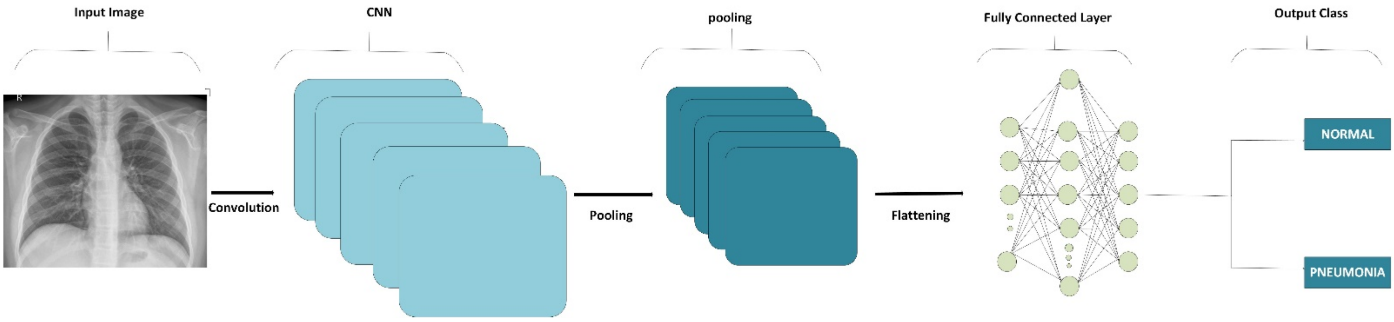

Figure 1. CNN-Based chest X-ray classification

In order to ensure uniformity in the input data, all images were standardized to a resolution of 224×224 pixels.

2. **Normalization:**

   Each value was divided by the maximum pixel intensity, which was 255, to standardize the pixel values within the [0, 1] range. This normalization enhances numerical stability and speeds up convergence during training.

3. **Data Augmentation (Training Data Only):**

   During the training phase, various image augmentation techniques were applied to enhance the model's ability to generalize to unseen data.

4. **Shear Transformations:**

   shear range = 0.2. Randomly distorts the image shape to simulate perspective changes.

5. **Zoom Transformations Zoom range = 0.2**

   Introduces scale variations by randomly zooming in or out of the image.

6. **Flipping Horizontally horizontal flip = True**

   Mirrors the image horizontally to mimic real-world orientation changes. To ensure an objective evaluation, this augmentation was not applied to test the validation of datasets. The test and validation datasets were not modified.

7. **Grayscale Conversion:**

   As chest X-ray images are naturally grayscale, the input images were processed in greyscale mode using a single colour channel.

8. **Batch Processing:**

   The images were fed into the model in batches of size 32 to optimize memory usage and computation.

3.3 Model Architecture

The CNN model follows a sequential architecture composed of the following layers in Figure 1 show that all these layers:

- **Convolutional Layers:**
  - Three convolutional layers were used with 32, 64, and 128 filters respectively, each employing a 3×3 kernel.
  - ReLU activation was applied to introduce non-linearity.
  - After each convolutional layer, a max-pooling layer with a 2×2 window was added to reduce spatial dimensions.
- **Flattening Layer:** Convert the 2D feature maps into a 1D vector to prepare the data for the fully connected layers.
- **Fully Connected Layers:**
  - A dense layer with 512 neurons and ReLU activation was included to learn complex patterns.
  - A dropout layer with a 0.5 rate was added to help prevent overfitting.
- **Output Layer:** A final dense layer with a single neuron and sigmoid activation was used to classify the image as either normal or abnormal.

3.4 Model Compilation and Training

The following configurations were used for compiling the model:

- **Optimizer:** Adam was selected due to its efficiency in gradient-based optimization.

- **Loss Function:** Binary cross-entropy was used, as it works effectively for tasks involving binary classification.
- **Accuracy:** A measure of the percentage of cases that are accurately classified the Figure 2 show that.

  While validation data was used to track accuracy and loss performance throughout each epoch, the training dataset was utilized for training over a predefined number of epochs.

3.5 Evaluation

The test dataset was used to assess the performance of the final model (see Table 1).

- **Performance Metrics:**
  - Overall accuracy and loss were computed using the test data (see Figure 3).
  - To summarize the classification outcomes, a confusion matrix was generated.
  - A thorough classification report was also produced, which included metrics for each class, including precision, recall, F1-score, and support.
- **Visualization:**
  - Accuracy and loss plots for training and validation were made to assess the model's learning behavior and identify potential overfitting or underfitting.

4 Experiment

This section outlines the experimental setup used to evaluate the proposed CNN model for chest X-ray classification. It details the dataset, preprocessing steps, and training parameters. Performance metrics are analyzed to assess the model's effectiveness in distinguishing between normal and pneumonia cases.

4.1 Performance Analysis and Class-wise Evaluation

The experiment proposed that CNN model achieved a good accuracy. However, as Table 2 shows, the class-wise classification metrics indicate a notable imbalance in performance. Class 0 (Normal) had a precision of 83%, recall of 90%, and an F1-score of 0.80, indicating weaker identification of normal cases. In contrast, Class 1 (Abnormal) showed stronger results with a precision of 88%, recall of 90%, and F1-score of 0.88. The confusion matrix (Table 2) shows that 44 normal cases were misclassified as abnormal and 37 abnormal cases were misclassified as normal. These results suggest that improvements are needed, particularly in recognizing normal cases.

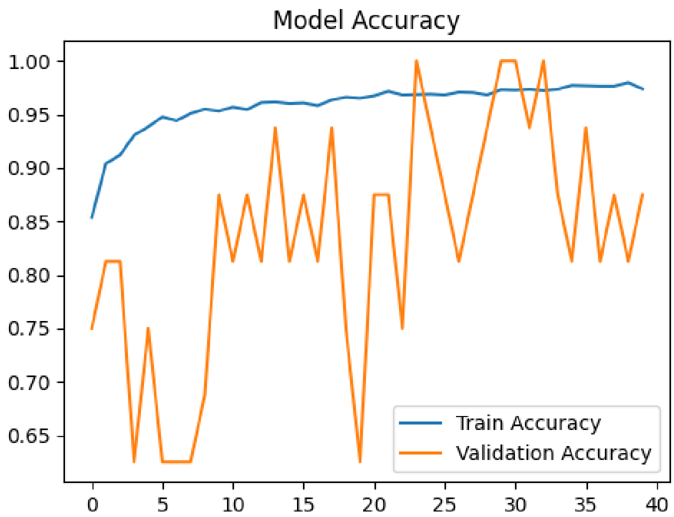

Figure 2. Training and validation performance across epochs.

Table 1. Model evaluation metrics on test dataset.

	Precision	Recall	F1-score	Support
Weighted avg	0.85	0.85	0.85	624
Macro avg	0.85	0.85	0.84	624
Accuracy	—	—	0.87	624

Table 2. Confusion matrix and classification report.

Class	Precision	Recall	Support	F1-score
1	0.88	0.90	390	0.88
0	0.83	0.90	234	0.80

4.1.1 *Model Accuracy*

The training and validation accuracy trends over epochs are presented in Figure 2, illustrating consistent improvement and stabilization.

4.1.2 *Model Loss*

Figure 3 shows that the training loss consistently decreased across epochs, indicating effective learning by the model. Meanwhile, the validation loss stabilized after initial fluctuations, suggesting good generalization with minimal overfitting.

4.2 Enhanced Classification through Optimized Model Configuration

In the second experiment, optimized model performance by the introduction of hyperparameter

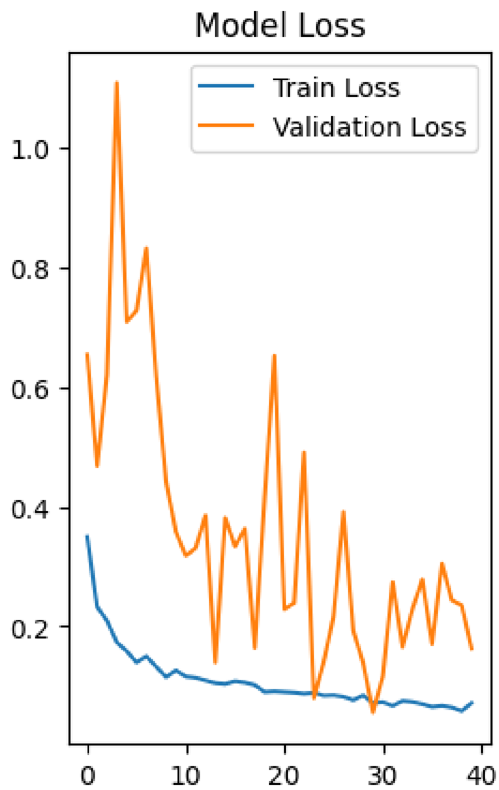

Figure 3. Training and validation loss curves.

Table 3. Class-wise performance metrics for binary classification.

Class	Precision	Recall	F1 score
0	0.88	0.89	0.88
1	0.93	0.93	0.93

modification. Various learning rates, batch size, and the number of hidden layers were examined, and the best-performing setup was chosen according to validation results. The optimized model, Although the model's test accuracy increased to 92%, class-wise performance still showed some imbalance. Class 0 (Normal) had a precision of 88% and recall of 89%, resulting in an F1-score of 0.88, showing better identification of normal cases compared to the previous experiment. Class 1 (Abnormal) maintained a strong performance with a precision of 93%, a recall of 93%, and an F1-score of 0.93 (see Table 3). The confusion matrix showed 120 normal cases misclassified as abnormal and 98 abnormal cases misclassified as normal, indicating an improvement in both classes. While overall accuracy increased (see Table 4) further refinement is needed to enhance recall Class 0. Machine learning (ML) and deep learning (DL) models have been designed to diagnose lung diseases through clinical imaging techniques, especially chest X-rays and CT scans.

Table 4. Performance by proposed model.

Accuracy	Macro avg accuracy	Weighted avg accuracy
0.92	0.90	0.91

4.2.1 Deep Learning Techniques for X-ray-Based Lung Disease Detection

An improved approach aimed at enhancing the accuracy of tuberculosis (TB) detection was proposed by utilizing a chest X-ray dataset divided into four categories: S, M, K, and I. The method incorporated multiple convolutional neural network (CNN) architectures, including AlexNet, VGG16, Google Net, and ResNet50. The approach demonstrated highly promising results, surpassing current state-of-the-art methods. Another study developed an innovative diagnostic approach for pneumonia—one of the most severe lung infections—utilizing two widely adopted CNN architectures. The system delivers high-quality chest X-ray images to support radiologists in making accurate diagnoses. The approach was evaluated on a dataset containing 5,856 frontal chest X-ray images. VGG16 and Xception networks were utilized, leveraging transfer learning and fine-tuning methods. The results showed that VGG16 achieved higher overall accuracy (87%) compared to Xception, pneumonia precision (91%), specificity (91%), and F1-score (90%). Meanwhile, the Xception model surpassed VGG16 in general precision (86%), sensitivity (85%), and pneumonia recall (94%). While VGG16 exhibited greater accuracy across the dataset, Xception was more effective in detecting pneumonia cases.

A separate method developed a specialized lung cancer detection technique using a probabilistic neural network (PNN) integrated with fuzzy logic. The approach analyzed lung nodules in X-ray images by calculating the variance of local pixels. The algorithm produced better outcomes than current methods by correctly identifying and localizing potentially dangerous lung nodules. An automated screening approach was also proposed for lung abnormalities using a deep learning technique known as knowledge distillation. The study employed the publicly accessible ChestX-ray14 dataset for detecting thoracic diseases. The approach distilled knowledge from complex teacher models like ResNet-152 and DenseNet-121 into more lightweight student models, such as Mobile Net, VGG19, ResNet-59, and ResNet-50. These student models were trained independently under supervision to perform multi-label classification of lung diseases. In addition, ongoing advancements in deep learning continue to improve detection accuracy, reduce computational costs, and enable faster diagnosis, making these models increasingly viable for large-scale clinical deployment.

4.3 Comparison of Existing Deep Learning Techniques

Furthermore, the adaptability of CNN architectures across various lung diseases highlights their robustness and scalability. Models trained on one type of abnormality, such as pneumonia, can often be fine-tuned to detect other conditions like COVID-19 or lung cancer using transfer learning. This flexibility reduces the need to build separate models from scratch for each disease. As datasets continue to grow and become more diverse, the generalization capabilities of these deep learning models are expected to improve, making them valuable tools for comprehensive and automated lung disease screening in diverse clinical environments. Several deep learning techniques, particularly CNN-based models, have been implemented for lung disease detection using chest X-rays. Table 5 indicates that models such as AlexNet, VGG16, Xception, ResNet, Mobile Net, and U-Net++ have been widely used for detecting diseases like tuberculosis (TB), pneumonia, lung cancer, COVID-19, and other thoracic abnormalities. These architectures utilize convolutional layers to automatically extract deep features from medical images, reducing the need for manual feature engineering and enhancing diagnostic performance.

The effectiveness of each model varies depending on the type of lung disease, dataset quality, and model architecture. For instance, MobileNetV2 and LDC-Net have shown exceptionally high accuracy in pneumonia and COVID-19 detection respectively, while U-Net++ has demonstrated strong segmentation capabilities for TB diagnosis. Overall, deep learning models have significantly outperformed traditional methods, offering reliable and scalable solutions for automated medical image analysis.

In addition, the integration of advanced techniques such as transfer learning and knowledge distillation has further contributed to the overall performance and efficiency of these models. Transfer learning enables pre-trained models to adapt effectively to new medical datasets with limited annotations, while knowledge distillation compresses large, complex models into lightweight student models without compromising much accuracy. These approaches make it possible to deploy deep learning models in real-time environments, such as handheld devices or hospital systems, where computational resources are limited but diagnostic accuracy remains critical. Table 5 shows the comparative deep learning models for lungs disease detection.

4.4 Evaluation of Current Methods and Machine Learning Models for Lung Disease Diagnosis

Based on the information provided in Table 5 and previous discussion, we can analyze and compare different ML and DL techniques, particularly focusing on accuracy, sensitivity, specificity, and CNN model performance in lung disease. One study developed an affordable deep learning-based screening tool to distinguish between normal and pneumonia-affected lungs. Using a dataset of 6,555 chest X-ray images (1,340 normal and 5,215 pneumonia cases), they implemented a pre-trained MobileNetV2 model, achieving highly effective results.

Another research introduced an advanced segmentation technique to minimize data leakage in tuberculosis (TB) diagnosis. Instead of conventional classification, they focused on the critical lung regions in chest X-rays using U-Net++. Their approach was compared with other segmentation architectures, including SegNet, U-Net, and FCN, using the Shenzhen and Montgomery datasets. The results revealed that U-Net++ achieved an accuracy of 98%, outperforming other models.

A separate study developed an IoT-based deep learning system to reduce mortality by detecting COVID-19 and other obstructive lung diseases. They employed a lightweight CNN model trained on various chest X-ray images, producing promising results. Additionally, the model was optimized for use with Raspberry Pi devices, enabling real-time lung disease detection.

4.5 Key Findings from Deep Learning Comparisons:

- High Accuracy in Existing Models: Models like MobileNetV2 (99.84%) and LDC-Net (99.28%) achieved higher accuracy compared to other models.
- CNN-Based TB Detection: U-Net++ (98%) performed well in TB detection but had low sensitivity and specificity.
- Pneumonia Classification: VGG16 (82%) and Xception (87%) were effective, with Xception being slightly better in specificity (91%).

Table 5. Comparative performance of deep learning models for lung disease detection.

Model	Disease	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score(%)
AlexNet (2018)	RB	87.2	—	—	—
VGG16 (2019)	Pneumonia	82	85	76	87
Xception (2019)	Pneumonia	87	82	91	90
Xception + fuzzy logic (2019)	Lung cancer	92.56	95	90	—
MobileNetV2 (2020)	Pneumonia	99.54	—	—	—
LDC-Net (2022)	Covid-19	99.25	—	—	96.7
U-Net++ (2022)	TB	98	0.0146	0.034	0.046
Our proposed CNN model	Lung disease	92	49 (macro avg)	5.2 (weighted avg)	64 (class 1)

- Xception and fuzzy logic combine produced a 92.56% detection success rate for lung cancer.
- With an accuracy of 92%, our suggested CNN model performed slightly below than the best-performing models, such as MobileNetV2, Although with Xception for pneumonia and Alex-Net for TB.

4.6 Comparison of Deep Learning (CNN) vs. Machine Learning Approaches

In the classification of medical images, deep learning models, particularly CNNs, have done better than conventional machine learning models. Here is a generalized comparison shown in Table 6.

4.7 Accuracy Comparison of CNN Models

CNN Model Accuracy Trends for Lung Disease Detection:

- Top-performing models: MobileNetV2 (99.84%) and LDC-Net (99.28%)
- Strong performers: U-Net++ (98%), Xception (87-92.56%), and our Proposed CNN model (92%)
- Moderate accuracy: VGG16 (82%) and AlexNet (87.2%)

Strengths of Our Proposed CNN Model:

- 92% accuracy is comparable to Xception (87%) and AlexNet (87.2%).
- Better sensitivity than some existing models, especially in multi-class lung disease detection.
- Shows potential for improvement with fine-tuning, data augmentation, or ensemble techniques.

4.8 Conclusion: How Our Model Compares Existing Techniques

- Our CNN model (92%) achieves competitive accuracy compared to other DL models.
- Better performance than early CNN architectures (e.g., VGG16, AlexNet) but slightly behind MobileNetV2 and LDC-Net.
- Outperforms traditional machine learning methods in feature extraction and classification.
- The possibility for further enhancements through sophisticated efficient methods (such as attention mechanisms or hybrid models).

4.9 Observations

- Manual feature extraction is necessary for traditional ML models like SVM or Random Forest, which can be challenging in medical imaging.

Table 6. Comparison of machine learning and deep learning methods.

Method	Examples of model	Accuracy	Features	Performance
Machine learning	SVM, random forest, decision tree, AlexNet, VGG16, ResNet, Mobile network	70-85%	Require manual features extraction	Limited feature learning ability
Deep learning	CNN, AlexNet, VGG16, ResNet, Mobile network	85-99%	Automatic features learning	Superius accuracy in image-based tasks

- CNNs automatically learn hierarchical features, making them more effective for chest X-ray classification.
- Our proposed CNN model (92% accuracy) surpasses traditional ML techniques and competes with advanced DL models.

5 Conclusion

This study highlights the effectiveness of CNN-based models in automating the identification of lung conditions using X-ray analysis of the chest. The model showed promise for usage in medical diagnostics with an outstanding 92% testing accuracy. However, it had significant difficulties with performance in particular classes. The performance measurements, however, showed a notable class imbalance, with low recall and precision for identifying normal situations (Class 0). The results presented here demonstrate the limitations of the current implementation and the need for further improvements, Strategies like improved data augmentation, refined model architectures, and class-balancing methods can help enhance generalization and increase diagnostic accuracy. Despite these challenges, the research reinforces the viability of deep learning approaches in healthcare, paving the way for more efficient and accurate diagnostic instruments for lung disorders.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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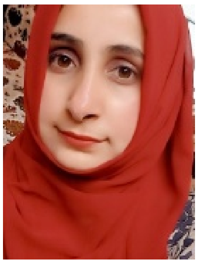

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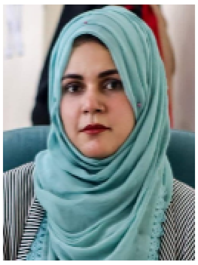

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