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Review Article

Prediction of Lung Diseases using Deep Learning Techniques: A Review

Sheikh Afaan Farooq* and Aleem Ali

Department of Computer Science and Engineering, University Institute of Engineering (UIE), Chandigarh University, Gharuan, Kharar, 140413 District Sahibzada Ajit Singh Nagar (Mohali), Punjab, India

ABSTRACT

Lung disorders remain at the centre of the burden affecting health on a global scale, and long-term respiratory complications caused by COVID-19 or other pulmonary disorders compound the burden. The accurate, timely identification of these disorders can improve the treatment outcome and diminish the number of fatalities. In recent years, the combination of deep learning techniques and feature selection methods has shown great promise in improving the accuracy and efficiency of medical imaging systems in diagnosis. This paper reports a systematic comparative review of the recent deep learning approaches to lung disorder diagnosis. The numerous works based on model architecture, feature selection strategies, datasets, performance metrics and clinical limitations are compared. In contrast to the current surveys that are largely focused on only a single disorder or a specific architecture, this review compares architectures, hybrid architectures and feature selection frameworks for the various lung disorders in a unified manner. Different models, such as DenseNet-121, Xception, InceptionV3, CNNs, Vision Transformers, MobileNet, RVCNet, EfficientNetB0, CNN-LSTM, XGBoost, Random Forest, and Decision Trees, are investigated. The results show that lightweight architectures like MobileNet and RVCNet can generally achieve better efficiency and accuracy, while more complex architectures and hybrid CNN-LSTM architectures can enhance the predictive performance. However, there are several challenges that are not yet addressed, such as mislabelling of public datasets, overfitting, lack of generalisation to unseen clinical data, lack of interpretability of complex architectures, and lack of ability to handle patients with pre-existing lung abnormalities. Also, multi-label classification systems are yet weak for overlapping pulmonary disorders.

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E-mail addresses:
saf95afaan@gmail.com (Sheikh Afaan Farooq)
aleem.e12948@cumail.in (Aleem Ali)
* Corresponding author

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These challenges underline the need for trusted datasets, easily interpretable hybrid frameworks and clinically usable, intelligent diagnostic systems for future works in lung disorder detection.

Keywords: CT scans, deep learning models, feature selection techniques, hybrid models, lung disorders, X-rays

INTRODUCTION

Lung Disease is a common problem globally, and its severity has worsened due to the excessive usage of smoking, alcoholic consumption, and dirty air quality Index. As per the WHO (World Health Organisation), around 3.9 million individuals lose their lives to lung disorders like chronic-obstructive pulmonary disorder (COPD), lung cancer, pneumonia, and Tuberculosis (TB) in the world. The COVID-19 disorder-related pandemic may be slacking off, but its effect remains and are a cause of a serious respiratory health issue. According to a study conducted by the Forum of International Respiratory Societies (FIRS), there are five respiratory-related issues that act as the most common and deadly issues of disease and fatality globally; these disorders are COPD, asthma, pneumonia, TB and lung cancer (Aykanat et al., 2020). The five deadly disorders specified above have resulted in billions of deaths worldwide in previous years, with only one disease, COPD, causing the deaths of three and a half million people in 2021 alone globally (Priyadarsini et al., 2023). The Spanish flu of 1918, which emerged as a devastating pandemic and the COVID-19 pandemic of 2019 are both related to respiratory diseases and led to the deaths of millions of people throughout the globe. Asthma, pneumonia, lung cancer, and TB are among the various lung conditions that affect individuals worldwide. The primary condition that prevents the lungs from working properly is respiratory disease. Mostly, there are three main types of lung disorders (Priyadarsini et al., 2023).

Airway Diseases

The airways or tubes that transport oxygen and other gases into and out of the body's lungs are impacted by several wide-ranging, connected illnesses (Mohammed et al., 2024). In most cases, they restrict the airway connections with the body and the environment. Asthma and chronic obstructive pulmonary disease (COPD) are examples of airway diseases (Priyadarsini et al., 2023). Chronic diabetic conditions can weaken the lungs and cause severe pulmonary infections (Abbasi et al., 2025). Lung cancer is also one of the most fatal disorders and involves limited diagnostic tools (Ansari et al., 2025).

Lung Tissue Diseases

These types of disorders affect the organisation of the lung tissues, making it harder for the lungs to inhale oxygen and exhale carbon dioxide (CO_2). Therefore, people under the influence of such lung disorders feel as if their upper body is caged inside compressed clothing (Casini et al., 2024).

Lung Circulation Diseases

These types of disorders affect the blood vessels responsible for the circulation of blood in the respiratory system. They are mostly caused by blood clotting and inflammation of the vessels. They can also cause a bad impact on the functioning of the heart (Casini et al., 2024). Most lung diseases are a subtype of the above three types.

The most fatal lung condition can be denoted as lung cancer, although being curable with early detection. Another major issue can be denoted as asthma, which causes the patients to have regular breathlessness. This condition also causes the airways to narrow and dilate, and this makes it tough for the patient to breathe normally and gives them the sense that they are not provided with sufficient air (Karaddi & Sharma, 2023). The most prevalent lung infection is pneumonia, which can be brought on by germs or viruses, such as the coronavirus that causes COVID-19. Acute respiratory distress syndrome (ARDS) is a dangerous condition that causes abrupt and severe harm to the lungs. One such instance is COVID-19. Until their lungs heal, many ARDS patients require assistance breathing via a device known as a ventilator. People with lung conditions should refrain from smoking, practice yoga, and engage in regular exercise (Casini et al., 2024).

An artificial intelligence (AI) technique called deep learning is utilised to train the computers to interpret information like that of the human brain (Büyükkeçeci & Okur, 2022). Deep learning algorithms may provide precise insights and predictions by identifying intricate patterns in text, audio, images, and other data (Doddavarapu et al., 2020). Deep learning techniques may be used to automate processes like picture description and sound file transcription into text that normally need human intellect (Yamashita et al., 2018). The main intent of this paper is to underline the current studies and attempts towards the utilisation of various hybrid and evolving deep learning techniques for the analysis of lung diseases globally.

Feature Selection

In machine learning, feature selection is one of the most important steps because it involves the process of choosing the relevant and most informative features from the dataset and discarding the others that are considered irrelevant or redundant (Ahmed et al., 2023). This is a very important step in model simplicity, operation enhancement and system resources reduction. Thus, due to ignoring unnecessary data, the model reduces the chance of overfitting, can deal with more complex data and is easier to understand (Rochmawanti & Utaminingrum, 2021). In any dataset, not all features aid the model in its prediction or classification tasks equally. Some may just contribute noise or may simply be redundant, leading to waste and deterioration of the model output. Feature selection determines these weak features and gets rid of them so that the model is built on the overlap of the characteristics that directly affect the target (Bharati et al., 2020).

Filter Methods

It serves to assess how useful features are, using stats instead of machine learning. They employ methods like correlation analysis, chi-square tests, and mutual information to sort features by their ability to predict outcomes. These approaches are quick and effective. They work great as an initial phase in choosing features ahead of using more sophisticated methods, as shown in Figure 1.

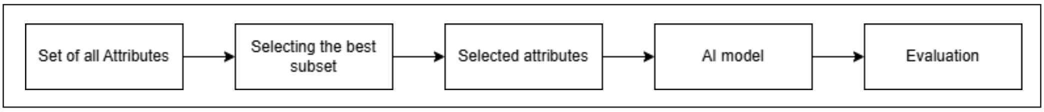

Figure 1. General overview of filter methods

Wrapper Methods

This, in contrast, chooses features by repeatedly training and assessing a machine learning model, as shown in Figure 2. Techniques such as forward selection, backward elimination, and recursive feature elimination (RFE) fit here. They indeed cost more in computational time. However, they tend to yield better accuracy since they account for how features interact with the target variable.

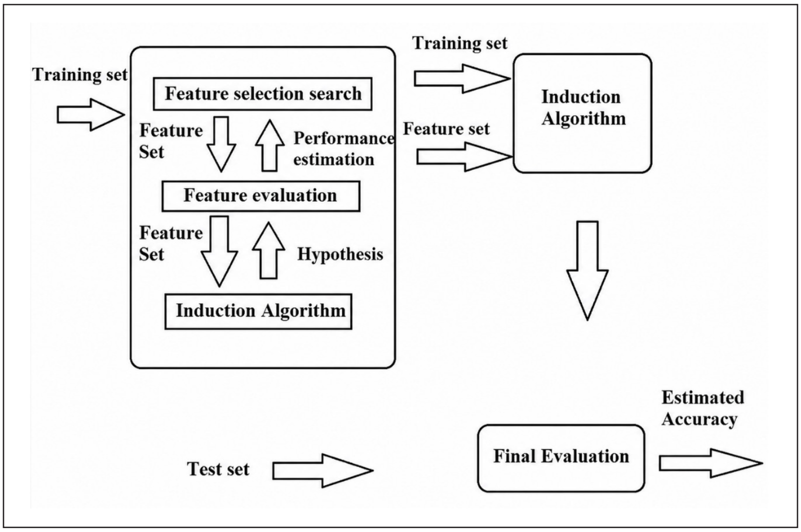

Figure 2. Wrapper method

Embedded Methods

Integrate feature selection in the model training process. For instance, lasso regression and tree-based methods do this by penalising features that don't matter or checking how important each feature is while training (Varshni et al. 2019). These methods also work very well since they then merge the strengths of both filter and wrapper approaches, as shown in Figure 3.

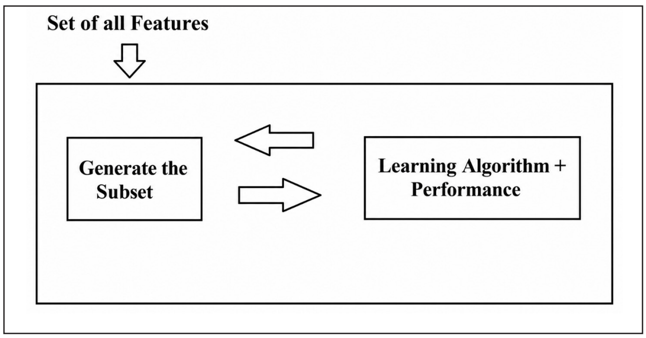

Figure 3. Embedded method

Performance Measure

The performance measures in artificial intelligence (AI) are the key metrics. They help to see how good the AI system is at reaching the goals (Souza et al., 2019). These measures count the effectiveness, the efficiency and the accuracy of the AI models. This way, the researchers and the developers can evaluate, then compare, and then enhance the performance (Shimja & Kartheeban, 2024).

The Types of Performance Measures in AI

Accuracy and Error Rates

- **Accuracy:** The ratio of correctly predicted instances and total instances (Eq. 1).

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad [1]$$

- **Error Rate:** The proportion of incorrect predictions (Eq. 2).

$$Error\ Rate = 1 - Accuracy \quad [2]$$

Precision, Recall, and F1-Score

- **Precision**: The ratio of correctly predicted positive observations to the total predicted positives (Eq. 3).

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP)\ +\ False\ Positives\ (FP)} \quad [3]$$

- **Recall (Sensitivity)**: The ratio of the correctly predicted positive observations to all the actual positives (Eq. 4).

$$Recall = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP)\ +\ False\ Negatives\ (FN)} \quad [4]$$

- **F1-Score**: It is the harmonic mean of precision and recall (Eq. 5).

$$F1 - Score = \frac{Precision * Recall}{Precision + Recall} \quad [5]$$

Confusion Matrix

It is a tabular representation of the actual versus the predicted outcomes in classification tasks, containing the True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) (Eq. 6).

$$Confusion\ matrix = \left[\frac{[True\ Positive] \quad [False\ Positive]}{[False\ Negative] \quad [True\ Negative]}\right] \quad [6]$$

ROC-AUC Curve

- **Receiver Operating Characteristic (ROC)**: It denotes the plot of true positive rate (TPR) against the false positive rate (FPR) at the various thresholds.
- **Area Under the Curve (AUC)**: It measures the ability of a model to distinguish between the classes. The higher AUC values indicate better performance.

Mean Squared Error (MSE) and Mean Absolute Error (MAE)

- **MSE**: It measures the average squared difference between predicted and actual values (Eq. 7).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Actual_i - Predicted_i)^2 \quad [7]$$

- **MAE**: Measures the average absolute difference between predicted and actual values (Eq. 8).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Actual_i - Predicted_i| \quad [8]$$

Logarithmic Loss (Log Loss)

It measures the performance of a classification model whose output is a probability value. The lower values indicate better performance (Eq. 9).

$$Log\ Loss = -\frac{1}{n}\sum_{i=1}^{n}(y_i\ log(\hat{y}_i) + (1 - y_i)log(1 - \hat{y}_i)) \quad [9]$$

R-squared (R^2)

It indicates the proportion of the variance in the dependent variable explained by the independent variables in the regression models; the values closer to 1 indicate a better fit (Eq. 10).

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad [10]$$

Cross-Validation Scores

The performance is measured by the splitting of data into training and testing subsets multiple times, for example, k-fold cross-validation.

Execution Time and Computational Efficiency

It measures the time and the resources required to train and execute the model.

Specific Metrics for Specialised AI Domains

- **BLEU Score**: It evaluates the quality of the machine translation models.
- **IOU (Intersection over Union)**: It measures the accuracy of the object detection models.
- **Perplexity**: It evaluates the language model by checking its ability to predict the sequences of the text.

The choice of the performance measures depends upon the type of the problem, the data characteristics, and the specific goals of the artificial intelligence (Tay et al., 2021).

Deep Learning Models and Techniques Used to Predict Lung Diseases

Deep learning techniques have significantly improved lung disorder detection through effective analysis of medical data. Neural networks are highly utilised for medical image analysis, particularly lung X-rays and CT scans, due to the ability to automatically extract the discriminative features associated with disorders like pneumonia, lung cancer and tuberculosis (Salau & Jain, 2019). Transfer learning has further added to these features by enabling the use of pre-trained models for imaging tasks, reducing the computational complexity and adding to the performance, especially when the labelled dataset is limited (Pemeena et al., 2023). Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) are effective for analysing the sequential clinical data, including the patient history and pulmonary records, thereby allowing prediction of disorder progression (Reddy et al., 2019). Autoencoders help in automated feature extraction and anomaly detection for the identification of rare pulmonary abnormalities. The hybrid architectures combining the CNNs and LSTMs increase predictive ability by integration of radiological images with patient medical history (Nabavi et al., 2021). Vision Transformers (ViTs) employing attention mechanisms underline the clinically relevant features, adding to feature representation and model accuracy. The integration of the advanced deep-learning approach with expertise in medicine enhances lung disorder prediction, thereby enabling pre-diagnosis, personalised treatment and improved patient result in practice (Tay et al., 2021).

DL Model

The deep learning technique to classify images involves the following steps.

Data Collection

The first step is to collect images and give them labels. The categories should be clear, and the images should be of good quality. It is essential to have varied examples for the model to perform effectively. The ethical sourcing matters, and there must be enough data for each class to avoid skewing results.

Data Preprocessing

The second step requires the images to be prepared for the deep learning model. They must be resized to a uniform dimension. The normalisation of pixel values is also crucial. Additionally, data augmentation techniques such as rotation, flipping, or adjusting brightness are necessary. The proper preparation ensures consistency and aids the model in handling diverse situations more effectively.

Model Selection

The third step involves choosing a proper deep learning model as a very important process. Suppose, for instance, CNN is a common method for image analysis. Other methods like ResNet, VGG, and DenseNet are also effective in extracting features from images. The choice depends on how big the dataset is, the complexity of the task, and the computing resources at hand.

Model Design

The fourth step details how the model appears, what layers it has, what activation functions are used, and how many classes it should output. Python, TensorFlow, or PyTorch is used for this task, as they are useful tools. The design must match the complexity levels, and there should be a balance between power and efficiency.

Training the Model

The fifth step involves the model finding patterns by decreasing the loss function, such as cross-entropy. Optimisers, like Adam, help adjust parameters gradually during training. The hyperparameters, including learning rate and batch size, also matter. This process continues over many epochs until good results are achieved.

Validation

The sixth step involves training, which is utilised to check the performance with new data, known as validation. It assists in adjusting the hyperparameters well and improves general skills. Techniques like early stopping and dropout can help resolve problems like overfitting, ensuring it stays effective for actual tasks.

Testing

The seventh step is used for testing. It is utilised to check how well the model performs on new data. The performance metrics, such as accuracy, precision, recall, and F1-score, provide insights into what is effective and what needs improvement. A confusion matrix also illustrates specific mistakes clearly, helping to direct future corrections.

Deployment

The eighth step involves using the model. Also, it involves the process of making it work with current software or systems, as compatibility is very important. Also, considering runtime limits is important because high latency can be frustrating when using models in real-world situations.

Post-Deployment Monitoring

The ninth step involves watching the model after releasing it, as it is important for good performance over time. The data distributions change, so retraining may need to happen regularly with new data as time goes on. Monitoring helps in catching problems quickly, allowing updates to ensure classification stays reliable and steady. Figure 4 shows the overview of all these steps.

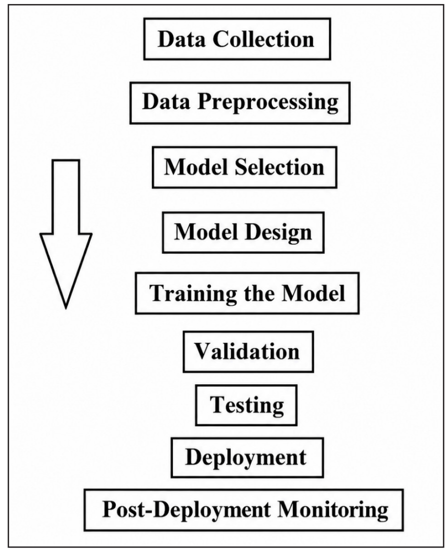

Figure 4. The steps involved in a deep learning model

Process for Diagnosing Lung Diseases Using Deep Learning Models

The explainable methods in artificial intelligence have improved the health-based diagnosis and medical analysis (Pabba et al., 2025). The lung disorder COPD is a severe and fatal disorder that weakens the lungs; however, the diagnostic methods for analysing this disorder have improved sufficiently (Abulizi et al., 2026). The diagnoses of the lung disorders involving deep learning (DL) models starts by use of efficient medical images, like chest X-rays or CT scans (Souid et al., 2021). These images are labelled by the experts in the medical field who identify conditions like pneumonia, tuberculosis, or lung cancer (Kieu et al., 2020). The next are the pre-processing steps, which involve the resizing, the normalisation, and the augmentation of the images for preparation towards analysis. It makes the data stronger, too (Mengistie & Kumar, 2021). A deep learning model is then selected. Usually, this is a Convolutional Neural Network (CNN). This works well because it extracts features from images effectively. Sometimes, pre-trained models like ResNet or DenseNet get tuned (Hurst et al., 2021). This is called transfer learning. It makes them fit better for certain datasets without needing a ton of computing power. In training, the model looks for patterns in labelled data. It tries to lower something called a loss function (Nadal-Martínez et al., 2026). An optimiser is utilised to change the parameters to make predictions better. Also, the validation takes place, which provides support for adjustment of the hyperparameters (Kumar & Kezia, 2024). This method helps in the avoidance of overfitting with methods like dropout. After the training of the data is complete, a check is done on how well the model works on the new data that it hasn't seen before.

Also, the utilisation of metrics such as the accuracy, the precision, the recall, and the F1-score is done to see how good it is. A confusion matrix helps point out specific errors made by the model (Abbas et al., 2021). When validation is done, the model is use in hospitals to assist doctors by offering quick and accurate diagnoses. Ongoing monitoring and periodic updates with new data help keep the model reliable (Tripathi et al., 2024). This way, it can adapt to changes in imaging technology and patient groups. Overall, this method boosts diagnostic accuracy as shown in Figure 5.

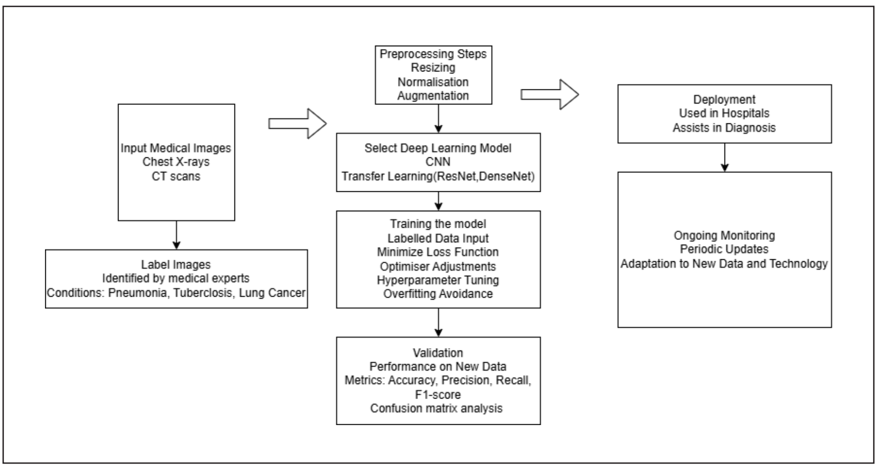

Figure 5. The review of the relationship between deep learning and lung disease detection

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a type of deep learning model that are made for working with structured data like images. This model is made up of layers built on basic gates that are termed as neurons, as shown in Figure 6.

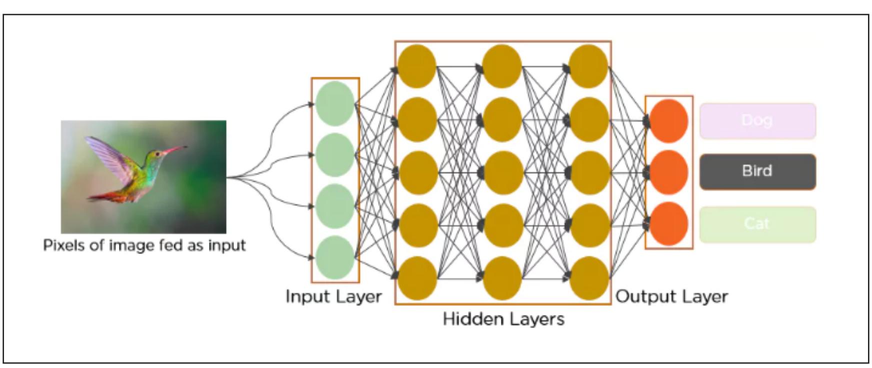

Figure 6. CNN model

The Main Parts of a CNN

Convolutional Layers

These layers are utilised to use filters on the image to create feature maps (Vikul et al., 2020). The filters can move over the image and identify features like the edges, textures, and shapes.

Pooling Layers

These layers are utilised to reduce the size of the feature maps. They can lower the dimensionality and help the network to be less sensitive to small changes in the input.

Fully Connected Layers

These layers do the high-level analysis based on the feature maps produced by the convolutional and the pooling layers.

Activation Functions

Usually, the RELU (Rectified Linear Unit) function is applied to add non-linearity.

- Formula for Convolutional Layer (Eq. 11):

$$f(x) = (x * w) + b \qquad [11]$$

where:

x is the input image or feature map.
w is the filter (kernel).
b is the bias term.
$*$ denotes the convolution operation.
$f(x)$ is the output feature map produced after applying the convolution.

- Formula for Pooling Layer (Max Pooling) (Eq. 12):

$$y = \max(x_1, x_2, \dots, x_n) \qquad [12]$$

where:

$x_1, x_2, \dots, x_n$ are the values within the pooling window.
y is the maximum value selected from the pooling region.

- Formula for Pooling Layer (Average Pooling) (Eq. 13):

$$y = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad [13]$$

where:

x_i represents each value in the pooling window.
n is the total number of values in the pooling region.
y is the average value of all elements within the pooling window.

Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) can be denoted as a type of neural network which tries to spot the patterns in the data that comes one after another, like the time series, text, or speech (Hussain et al., 2020). Unlike the normal feedforward neural networks, the RNNs have loops that allow the information to stick around, which is super important for dealing with the data that flows in a sequence (Wang et al., 2023).

The Main Parts of the RNNs

Input Layer

It takes the sequence data in the model.

Hidden Layer

It has units that loop back, using input and the last hidden state to keep information from before as stored.

Output Layer

It provides the results for each time step.

The hidden state h_t at time t is computed as (Eq. 14):

$$h_t = f(W \cdot h_{t-1} + U \cdot x_t + b) \qquad [14]$$

where:

h_t: Hidden state at time t.
h_{t-1}: Hidden state from the previous time step.
W: Weight matrix associated with the previous hidden state.
U: Weight matrix associated with the current input.

x_t: Input vector at time t.
b: Bias term.
f: Activation function (commonly tanh or ReLU).

- The output y_t at time t is computed as (Eq. 15):

$$y_t = g(V \cdot h_t) \tag{15}$$

where:
y_t: Output at time t.
h_t: Hidden state at time t.
V: Weight matrix associated with the output layer.
g: Output activation function (commonly Softmax for multi-class classification or Sigmoid for binary classification).

Long Short-Term Memory (LSTM) Networks

The Long Short-Term Memory (LSTM) networks are a type of improved Recurrent Neural Network (RNN) that aims to fix the problems observed in the regular RNNs (Chen et al., 2019).

Key Components of LSTMs

Cell State

A memory cell used for carrying information across the time steps.

Gates

The LSTMs have three gates that can control the flow of the information.

- **Forget Gate**: It decides what information to discard from the cell state.
- **Input Gate**: It determines which new information is added to the cell state.
- **Output Gate**: It controls the output based on the cell state.

1. The forget gate output at time t is computed as (Eq. 16):

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{16}$$

where:
f_t: Forget gate output at time t.
W_f: Weight matrix for the forget gate.

h_{t-1}: Hidden state from the previous time step.
x_t: Input vector at time t.
b_f: Bias term for the forget gate.
$[h_{t-1}, x_t]$: Concatenation of the previous hidden state and current input.
$\sigma(\cdot)$: Sigmoid activation function.

2. The input gate and candidate cell state are computed as (Eq. 17 and Eq. 18):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad [17]$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad [18]$$

where:
i_t: Input gate output at time t.
$\tilde{C}_t$: Candidate values for the cell state.
W_i: Weight matrix for the input gate.
W_C: Weight matrix for the candidate cell state.
h_{t-1}: Previous hidden state.
x_t: Current input vector.
b_i: Bias term for the input gate.
b_C: Bias term for the candidate cell state.
$[h_{t-1}, x_t]$: Concatenation of the previous hidden state and current input.
$\sigma(\cdot)$: Sigmoid activation function.
$\tanh(\cdot)$: Hyperbolic tangent activation function.

3. The cell state at time t is updated as (Eq. 19):

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad [19]$$

where:
C_t: Updated cell state at time t.
C_{t-1}: Cell state from the previous time step.
f_t: Forget gate output.
i_t: Input gate output.
$\tilde{C}_t$: Candidate cell state.

4. The output gate and hidden state at time t are computed as (Eq. 20 and Eq. 21):

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad [20]$$

$$h_t = o_t \odot \tanh(C_t) \quad [21]$$

where:

o_t: Output gate activation at time t.

h_t: Hidden state (output) at time t.

W_o: Weight matrix for the output gate.

h_{t-1}: Previous hidden state.

x_t: Current input vector.

b_o: Bias term for the output gate.

C_t: Updated cell state.

$\sigma(\cdot)$: Sigmoid activation function.

$\tanh(\cdot)$: Hyperbolic tangent activation function.

Transformer Models

The Transformer models are a type of deep learning model that have changed the field of natural language processing (NLP) and all the other tasks involving sequential data (Sah, 2020). They were first initiated in 2017. The transformers use the attention mechanisms to connect to the inputs and outputs globally, removing the requirement for recurrent or convolutional layers (Kondamuri et al., 2024).

Self-Attention Mechanism

This allows the model to focus on the various parts of the input sequence to understand the relationships between the elements, no matter how far apart they are in the sequence.

Multi-Head Attention

This builds on the self-attention by allowing the model to visualise the information from the different representation subspaces at the same time.

Position-Wise Feed-Forward Networks

This utilises a fully connected feed-forward network for each position in the sequence separately and in the same way.

Positional Encoding

This adds details about where each of the elements is in the sequence since the model does not naturally recognise the order.

1. The scaled dot-product attention is computed as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where:

Q: Query matrix.

K: Key matrix.

V: Value matrix.

K^T: Transpose of the key matrix.

d_k: Dimension of the key vectors.

$\sqrt{d_k}$: Scaling factor to stabilise the attention scores.

$\text{softmax}(\cdot)$: Activation function that converts attention scores into probability weights.

2. Multi-Head Attention (Eq. 22)

$$\text{MultiHead}(Q, K, V) = \text{Concat}(head_1, \ldots, head_h)W^O \qquad [22]$$

where (Eq. 23):

$$head_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \qquad [23]$$

where:

Q: Query matrix.

K: Key matrix.

V: Value matrix.

$head_i$: Output of the i^{th} attention head.

W_i^Q: Query weight matrix for the i^{th} head.

W_i^K: Key weight matrix for the i^{th} head.

W_i^V: Value weight matrix for the i^{th} head.

W^O: Output projection weight matrix.

Concat(·): Concatenation of all attention heads.

3. Position-Wise Feed-Forward Network (FFN) (Eq. 24):

$$\mathrm{FFN}(x) = \max(0, x\mathrm{W}_1 + \mathrm{b}_1)W_2 + b_2 \quad [24]$$

where:

x: Input feature vector.

W_1, W_2: Weight matrices of the two fully connected layers.

b_1, b_2: Bias vectors.

max(): ReLU activation function.

4. Positional Encoding (Eq. 25 and Eq. 26):

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right) \quad [25]$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right) \quad [26]$$

RESULTS AND DISCUSSIONS

Comparison of the Accuracy of Various Models

From the study of various literature, a mixture of deep learning-based techniques was analysed and utilised for the identification of lung diseases, where different approaches provided different performance measures. Table 1 presents the models and their accuracy used in lung disease detection.

Veeramani et al. (2025) utilised the explainable deep-learning framework through transfer learning and the U-Net segmentation for an accurate diagnosis of various lung disorders. Sabry et al. (2024) employed a DL or sound-audio-based model to identify various lung illnesses. The proposed method allowed for the analysis of recording length, noise contamination, and graphical representation through lung sound-based audio diagnosis. The research paper focused on an algorithm for lung assessment based on audio sound classification using ML techniques. This algorithm operated with multiple datasets, feature extraction techniques, pre-processing methods, artefact removal techniques, lung-heart sound separation, DL algorithms, and other models. Al-Qaness et al. (2024) proposed a model using a specific Chest X-ray scan image dataset. The objective was to utilise DL and ML models to analyse these X-ray images and detect lung diseases. These models demonstrated significant accuracy and efficiency in identifying lung diseases through CXR imaging. However, the survey on this dataset was not very helpful due to the unavailability of analysts working on lung disease datasets and the improved patient outcomes or, in other words, the accuracy of the dataset analysis. The primary purpose of this research was to identify lung diseases accurately, efficiently, and precisely and to explore advanced tools for detecting lung-related issues. The existing models provided a foundation, but researchers and scientists worked on improving algorithms to enhance their accuracy. The accuracy, models used and preprocessing methods utilised by these studies are shown in Table 1.

Table 1
Accuracy of various methods utilised for lung disorder detection

Author Name	Preprocessing Method	Model Used	Accuracy
Sungheetha et al., 2026	Resampling, Windowing, Segmentation, Normalisation	CNN + LSTM + Transformer Ensemble (Explainable Digital Twin Framework)	94.7%
Kamala & Mohan, 2026	Resizing (224×224), Gaussian Denoising, Data Augmentation (zoom=0.3, shear=0.3, vertical flip), Feature Normalisation, PCA-based Feature Fusion	GLCM + SIFT + MobileNet Hybrid Model	98.34%
Veeramani et al., 2025	Image resizing (256×256), normalisation, image augmentation (zooming, shearing, horizontal flipping), and improved U-Net lung segmentation	Proposed XAI-TRANS (InceptionV3 + XAI + Improved U-Net)	97.53%
Pham & Hoang, 2024	Local Feature Extraction with CNN Global Feature Modelling with Vision Transformer	CNNs and ViTs in a hybrid architecture	86.4%
Al-Rawe & Tekerek, 2023	Simple Image Preprocessing done manually	CNN MobileNet DenseNet	94% 78% 96%
Alam et al., 2023	Simple Image Preprocessing done manually	RVCNet	91.27%

Table 1 (*continued*)

Author Name	Preprocessing Method	Model Used	Accuracy
Syamala et al., 2023	Simple Image Preprocessing done manually	Decision Trees EfficientNetB0	96.90% 86.18%
Moura et al., 2022	Histogram Equalisation Radiomic Feature Extraction	Random Forest XGBoost	77% 82%
Wang et al., 2021	Image clipping, normalisation, and segmentation	CNN-LSTM	91.7%

Papavassiliou et al. (2026) in their work analyse the utilisation of artificial intelligence techniques for lung disorder diagnosis and analyse the limitations, such as less generalised datasets and low-performance metrics. Vinta et al. (2024) developed lung disease morbidity, and mortality are greatly impacted by interstitial lung diseases (ILD), a collection of illnesses involving interstitial fibrosis and inflammation. Early ILD classification examinations were challenging and time-consuming when several illnesses had similar clinical symptoms. Recent studies have produced impressive results in categorising medical pictures using deep learning algorithms. Using an enhanced U-Net++ model to segment the lung section of HRCT images, the researchers created a hybrid deep-learning network model for ILD classification. To segment the lungs with lung abnormalities, the U-Net++ module has been enhanced. Five different ILD classes are classified by the feature extraction procedure using a Refined Attention Pyramid Network (RAPNet) and a MobileUNetV3. Pham and Hoang (2024) provided a novel DL method that combines CNN and ViT to increase the effectiveness of diagnosing pneumonia from medical photos. To record localised connections on the inputs, the raw pictures were first run through a local filter. Two 3 × 3 convolutional layers were part of the local filter block. Before being supplied to the ViT block's patching layer, this local filtering technique seeks to improve rich characteristics. The benchmark dataset of chest X-rays was used to test the suggested approach. ViT, VGG19, Resnet50, and Densnet201 were among the well-known models that were assessed and contrasted with the suggested approach. Moreover, the accuracy of the suggested CNN and ViT-based technique is around 1% greater than that of the regular ViT model, and it is approximately 2% higher than VGG19, Resnet50, Densnet201, and smaller in model architecture, according to data from experiments. Al-Rawe and Tekerek (2023) applied the classification-based method algorithms on DL to identify lung-related infections or diseases caused by coronavirus using CXR images. In its study regarding lung infections, at least two algorithms were employed to identify or detect novel coronavirus disease using CXR image scans. These two models are known as Mobile Net and Dense Net, which are DL models. Many use cases have been made with the help of the Mobile Net model, and the case modelling approach attained an accuracy of 96%. The Area under the Curve has also achieved an accuracy level of 94%.

Alam et al. (2023) described this research paper with the help of a hybrid DL model to detect COVID-19 patients. The researcher used the X-ray image dataset for image recognition for future analysis as a precautionary measure for COVID-19 patients, so that they are less affected with the help of predictive analysis. This DL model was created by integrating three distinct DL architectures: ResNet101V2, VGG19, and a standard CNN model. This model was also applied to non-COVID patients, viral pneumonia patients, and normal lung-infection patients with the help of image processing techniques. This algorithm achieved an accuracy of 96% using various algorithmic approaches. This is one of the most suitable options, and it performs better than other algorithms. GRAD-CAM is an application tool that evaluates images with the help of the RVCNet framework. Syamala et al. (2023) focused on diagnosing the severity of diseases in patients and determining whether the condition is dangerous or moderate for the affected person. In this context, users could check a chest X-ray (CXR) image and perform cross-verification. Users could also upload pictures and check results using this data analysis. The input from a user could be either a string or an image. The research author aimed to detect chronic lung infections or diseases quickly, focusing on finding recovery and survival plans for patients as early as possible. The research analyst employed the Hypothesis (H0) approach in this study. The research team used predictive models such as DL and machine learning (ML); this paper explored the diagnoses of diseases such as novel coronavirus, tuberculosis, pneumonia, and COPD. After analysing COVID-19 and COPD, they achieved accuracies of 96.90% and 90.32%, respectively, by applying classification algorithms to these diseases. For the image dataset, they achieved an accuracy of 98.58% using the Efficient Net B0 DL algorithm. Devi et al. (2022) diagnosed lung diseases using ML and feature selection techniques based on a review explained by the author in this research article. The author covered almost all ML algorithms in this review, including both supervised and unsupervised ML algorithms. For example, Random Forest (RF) was highlighted as a supervised ML technique, while KNN was defined as an unsupervised ML technique. These algorithms were studied or surveyed by the author between the years 2020 and 2021. They were utilised to identify lung diseases using accuracy, precision, recall, sensitivity, and F1-score metrics. These models are still utilised to solve real-world problems involving incomplete, inaccurate, and varied data values in a dataset.

Moura et al. (2022) proposed chest radiographs of COVID-19 pneumonia and various lung infections by applying models of random features and classification techniques. The primary objective of this study was to identify the radiographic characteristics of COVID-19 through supervised ML algorithms Grounded in an approach called Shapley Additive Explanations (SHAP). SHAP was also used to implement selected features with cross-validation. A random search technique was employed to optimise the XGBoost and Random Forest algorithms. The boosting algorithm achieved an accuracy level of 82%.

The explanation highlights the significance of the middle left and superior right lung regions in diagnosing pneumonia caused by COVID-19, distinguishing it from different lung patterns. Kabiraj et al. (2022) suggested a CX-Ultranet (Chest X-ray Ultranet) that uses a multiclass cross-entropy loss function on a compound scaling framework to categorise and diagnose thirteen thoracic lung illnesses from chest X-rays. On the NIH Chest X-ray Dataset, the CX-Ultra net achieves 88% average prediction accuracy in around 30% less time than previous models. Setting a new standard in disease diagnosis from chest X-rays, the proposed CX-Ultra net effectively addresses class imbalance issues. It requires much less training time regarding floating-point operations per second. The performance metrics of related studies were also analysed, as shown in Table 2. The graph clearly shows that the accuracy of the models based on the algorithms Decision Tree, DenseNet, CNN, MobileUNetV3, and DualFCM perform exceptionally well and are comparable to each other when it comes to accuracy. The models powered by the algorithms Xception, InceptionV3, EfficientNetB0, XGBoost and RVCNet also perform well as compared to the models which are built on Hybrid CNNs and ViTs, MobileNet and Random Forest. Figure 7 shows the performance of various machine learning and deep learning-based algorithms based on the performance metric accuracy.

Table 2
The performance metrics of various methods utilised for lung disease detection

Author Name	Classification Technique	Accuracy	Precision	Recall	F1 score
Sungheetha et al., 2026	Explainable AI Digital Twin Framework (CNN + LSTM + Transformer Ensemble with SHAP/LIME)	94.7%	87.6%	91.2%	89.4%
Kamala & Mohan, 2026	Hybrid AI Model (GLCM + SIFT + MobileNet)	98.34%	98.33%	98.00%	98.00%
Vinta et al., 2024	Improved MobileUNetV3	97.31%	98.65%	98.05%	98.13%
Pham & Hoang, 2024	CNNs and ViTs in a hybrid architecture	86.4%	85.7%	87.2%	86.4%
Alam et al., 2023	RVCNet	91.27%	90.48%	98.30%	94.23%
Veeramani et al., 2025	Proposed XAI-TRANS (InceptionV3 + XAI + Improved U-Net)	97.53%	98.95%	97.01%	97.97%

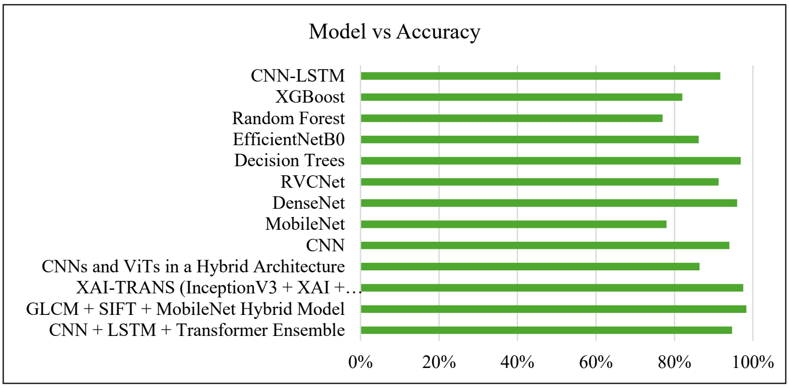

Figure 7. Specific classification model and its accuracy

Tripathi et al. (2021) proposed a DL model called CNN, which is used for classifying chest disease. The CNN model combined a convolutional layer, ReLU activations, a pooling layer, and a fully connected layer. The final fully connected layer contains 15 output units. Moreover, every output node is predicted to be one out of 15 diseases. A dataset, namely an X-ray dataset, was used to write a research article. This includes fifteen classes: Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Consolidation, Oedema, Emphysema, Fibrosis, Pleural Thickening, Hernia, and a class for images without any findings. These classes were utilised to train the model for lung disease prediction. Still, this model has given us beautiful results and a desired output. The accuracy of the results was predicted to be 89.77% with the help of classification algorithms. The model demonstrates the effectiveness of comparative analysis. Wang et al. (2021) suggested an integrated deep-learning method that can be used to reliably identify lung nodules using low-dose computed tomography (CT) and estimate the probability of developing lung cancer in the future. The approach balances the amount of positive and negative samples by using preprocessing methods such as picture cropping, normalisation, and segmentation (Rana et al., 2024). Khehrah et al. (2020) described lung tumours as a common cancer with a high incidence and fatality rate that are frequently discovered after the fact. The condition is diagnosed with computed tomography (CT) scans, and early detection computer-aided techniques are being developed. An algorithmic framework for lung CT scan nodule detection is presented in this research. Internal structures are recovered from the parenchyma, morphological operators are used to refine the histogram, and the lung location is isolated. Using a threshold-based method, candidate nodules are distinguished from other structures, such as bronchioles and blood arteries. Nodule feature vectors are created by extracting statistical and shape-based features, which are then categorised using support vector machines. In the first stage of lung disease, a process, namely Binarisation, is used to revert the images into the binary format, and after that, those pictures need to be compared with the threshold level for identifying lung tumours. In the next phase, CT scan images needed to be divided, preceded by a method which is known as the robust-feature extraction method, to determine the characteristics of the divided images to find the lung diseases. This model gives an accuracy of 96.67%. Figure 8 shows the year-wise comparative analysis of the classification performance metrics through the years 2023 to 2026.

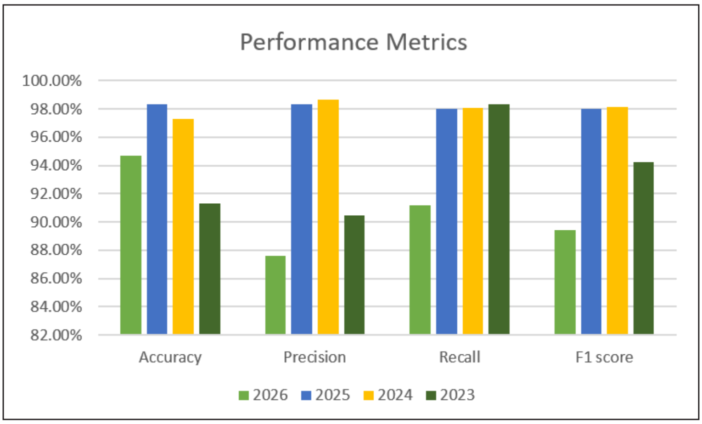

Figure 8. Trend analysis of classification metrics across multiple years

CONCLUSION

In this review, various deep learning techniques are studied and their applications to predict lung diseases are evaluated. Several deep learning techniques are evaluated, and their performance is measured. The hybrid architectures, like CNN-LSTM, performed better when the lung-disorder-based images were utilised to train the model. The deep learning models built on the CNN also performed with good accuracy. Deep learning has shown some promise in detecting lung diseases, though it still hasn't been really put to work in everyday clinical settings. A few issues, like unbalanced data, bias in selection, and high variance, tend to decrease the model's overall performance. This review concludes that research on lung disorder detection can be more effective when the following steps are followed,

- The selection of the data sources that are not only reliable but genuinely supply high-quality medical images.
- Identify which specific features really boost prediction accuracy.
- Select the features from the dataset that matter most.
- Choose a deep learning method that consistently performs best when it comes to detecting lung diseases.

PREPRINT

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It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

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