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PAPER

Advanced Deep Learning Integration for Early Pneumonia Detection for Smart Healthcare

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ABSTRACT

The surveillance of symptoms related to pneumonia is increasingly crucial due to its widespread occurrence and similarity to symptoms exhibited in other contagious diseases such as influenza, respiratory syncytial virus (RSV), and COVID-19. The timely identification of pneumonia can significantly diminish mortality rates. To tackle this issue, a pioneering non-contact technique for monitoring pneumonia symptoms has been developed. This investigation mainly concentrates on the early detection of pneumonia, which can serve as an indicator of the onset of other persistent ailments. The technique entails an analytical approach to scrutinize symptoms such as cold, cough, chills, sore throat, altered respiratory rates, and elevated body temperature by employing depth imaging methods. The crux of this exploration lies in the utilization of a combination of convolutional neural networks (CNN) and long short-term memory (LSTM) networks to classify video images in order to identify symptoms associated with pneumonia. The proposed model has showcased an impressive overall accuracy rate of 98.02% along with a significantly optimized prediction time of a mere 8.63 ms. Moreover, the study encompasses a comprehensive evaluation of various deep learning techniques in the detection of diseases exhibiting symptoms akin to pneumonia. The study introduces a pivotal advancement in medical diagnostics, emphasizing the importance and effectiveness of a fusion-based, profound learning system in the non-contact identification of pneumonia symptoms. This innovative approach has the potential to revolutionize the way pneumonia and similar diseases are diagnosed and monitored.

KEYWORDS

convolutional neural network (CNN), pneumonia, virus detection, pneumonia symptom surveillance, non-contact monitoring technique

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1 INTRODUCTION

Deep learning in medical imaging will enable real-time automated image feature annotation, selective data synthesis, and pixel-level classification. This is particularly important for pneumonia, a serious lung infection causing significant morbidity and mortality. Traditional diagnostics, such as chest X-rays and clinical evaluations, often have low sensitivity and specificity, leading to delayed diagnosis and therapy. Deep learning, based on neural networks with multiple layers, promises to improve diagnostic accuracy and efficiency, ultimately improving patient care. Pneumonia, a disease with variable symptoms, is challenging to diagnose due to its variability. It affects millions of people annually, particularly children and elderly individuals. Early diagnosis is crucial for improving prognosis and reducing mortality. Super deep learning techniques, particularly convolutional neural networks (CNNs), have shown potential in medical fields, particularly for image-related diagnostics, such as analyzing chest X-rays [1] and CT scans. These models have shown impressive performance in analyzing these types of diseases. CNNs can identify patterns in pneumonia by learning features from large volumes of labeled medical images. This automated analysis aids radiologists and clinicians in making faster diagnoses and facilitating quicker intervention. The deep learning model requires a massive dataset of annotated medical images, such as chest X-rays and CT scans, to train. It differentiates between normal lungs and those infected with pneumonia, as well as other diseases such as tuberculosis or COPD. Deep learning models are being used to detect pneumonia by analyzing medical images. As more data is provided, these models improve their diagnostic capabilities, making them more accurate and robust. They can also offer heat maps or attention maps that illustrate the most predictive parts of a medical image for pneumonia, making decisions more interpretable and increasing trust between detection algorithms. Deep learning can also be combined with other data sources such as electronic health records or clinical notes to provide a synchronized evaluation of patient status. This multi-modal approach allows deep learning to analyze and process different types of data, providing a more comprehensive view and increasingly accurate diagnosis. However, deep learning faces challenges that must be addressed. Deep learning models for pneumonia detection require high-quality medical image datasets and improved training data diversity. privacy concerns must be managed, and implementing these technologies requires careful planning and collaboration between technologists, clinicians, and healthcare administrators. Advanced deep learning technologies, such as and multi-modal data integration, can improve accuracy and efficiency in pneumonia diagnosis, reducing patient casualties and reducing health system burden through quick decision-making. AI-driven healthcare solutions are revolutionizing medical diagnostics by combining genetic insights and understanding human traits. This approach identifies and tracks a prevalent and hazardous disease, pneumonia, using advanced technology and deep learning. This technology has significant global health implications, transforming the detection and treatment of pneumonia.

The paper is divided into sections, including related work, proposed methodology, proposed model, results analysis, and conclusion. It reviews existing literature on chest X-ray analysis, presents the proposed deep learning model's architecture and data processing flow, evaluates the model's performance, and concludes with a summary of findings and suggestions for future research.

2 RELATED WORK

This study compares deep learning techniques for disease detection, focusing on symptoms, machine learning, and data sources. neural networks classify disease symptoms, leading to diagnosis. Colizza et al. highlighted the importance of aviation networks in monitoring and forecasting disease spread, highlighting the structure and intensity of these networks for global disease spread and public health policy improvement [2]. Jia et al. proposed data-driven analysis of pneumonia transmission dynamics that highlights the significant role of human movement patterns in infectious disease spread, influencing public health policy and management [3]. Lavezzo et al.'s study on the SARS-CoV-2 pandemic in Vo', Italy, highlights the importance of isolation, contact tracking, and thorough testing in controlling the virus [4]. Zhang et al.'s study evaluated Singapore's response to the 2015 MERS outbreak in South Korea, emphasizing swift action, ongoing observation, and coordinated international responses, improving disease prediction accuracy [5]. Table 1 compares features, machine learning algorithms, data-set sources, and diseases, highlighting symptoms similar to pneumonia disease and its noncontact-based detection method. Zuccon et al. utilized deep learning techniques to automatically detect influenza tweets in Australia using a dataset. Deep learning-based picture categorization algorithms are revolutionizing medical diagnoses, particularly in lung ailments, with CNNs providing more accurate imaging and enhanced diagnosis capabilities [6]. Benzebouchi et al. use a fusion-based multi-classification strategy for COVID-19 detection, a significant trend in medical imaging research, focusing on timely and accurate diagnosis during the pandemic [7].

In another work, Agarwal et al. discuss deep learning algorithms for lung disorder classification using a voting-based approach [8]. On the other hand, Haq et al. highlight transfer learning, a method that uses models trained on large datasets for specific tasks, especially in medical imaging, where large datasets are often lacking [9].

In a study, Albalawi et al. analyze deep learning methods for lung disease classification, emphasizing the importance of comparing AI approaches for medical diagnostics [10]. Jain and Jain explore AI's potential for detecting lung diseases, highlighting the growing interest in applying AI techniques to lung-related diseases, including COVID-19 [11]. Kundu R, et al. trained three convolutional neural network models, GoogLeNet, ResNet-18, and DenseNet-121, using deep transfer learning, weight distribution techniques, and channel-attention-based feature fusion for enhanced integration [12]. The study in [13] used a channel-attention-based feature fusion method, a residue block, and a self-attention module to enhance the model's integration, focusing on healthy individuals with pneumonia.

2.1 Data-set comparisons

Table 2 presents a non-contact-based dataset for classifying pertussis patients using cough sounds. It includes patient age, disease type, recording equipment, chest location, and other attributes. The dataset can be used for further experiments and research on cough recordings. In Tables 2 and 3, the study supports a non-contact survey for cough detection using breath-rate analysis, focusing on ECG, heart rate, respiratory level, blood oxygen saturation, and impedance signal. The dataset includes images and videos from an infrared camera, accurately detecting body temperature and pneumonia patients. In Table 4, attributes of BIDMC PPG and respiration dataset [23] as a contact-based method. Table 5: FLIR thermal dataset as a non-contact-based method.

Table 1. Comparison of studies focused on the detection method of diseases using deep learning

Study	Features	Machine Learning Model	Data-Set Source	Disease
[14]	Fast breathing, Body-ache, Chill, Nausea, Sore-throat.	Artificial Neural Network	Records of Pneumonia	Pneumonia
[15]	Headache, Myalgia Arthralgia, Retro-ocular pain Sickness, cough, and dyspnea.	ANN-MLP, ANN-RBF, SVM linear, and SVM-Gaussian	Dengue disease sample collected from the Paraguay.	Dengue
[16]	Symptoms based on different environmental conditions.	LSTM, DNN, OLS & ARIMA	Korea Meteorological Administration's weather information portal.	Generalized Infectious disease
[17]	Fatigue detection	CNN	CEW data-set.	Generalized Infectious disease.
[18]	Fever, Nausea, Vomiting, Diarrhea, Headache, Pain Abdomen, Muscular Pain	Artificial Neural Network	N/A	Dengue.
[19]	Whooping sound detection	Cough-Based Algorithm	Data-set consists of recordings of Pertussis-based and non-pertussis patients.	Pertussis
[20]	Cough Samples	Classic machine learning classifier (CML-MC)	ESC-50 data-set.	Corona Covid-19
[21]	SARS coronavirus and use of synthetic nucleic acid.	Real-time RT-PCR	Clinical specimens consist of a spectrum of human respiratory viruses.	Corona Covid-19
[22]	Severe acute respiratory syndrome	Artificial Neural Network	Pneumonia X-ray image database.	Corona Covid-19

Table 2. Description of Data-set for Pramono et al. [24]

S. No.	Attribute	Description
1.	Source Link	Link for the particular cough sound file.
2.	Disease	Type of disease.
3.	Age Group	Age of the patient.
4.	Length	Length of the recording.
5.	Number	Classification number assigned for Training Data/Test Data.

Table 3. Description of Dataset for Rocha BM et al. [25] study as a non-contact-based method

S. No.	Attribute	Description
1.	Patient Number	Serial Number assigned to the patient.
2.	Recording Index	A number of recordings arranged in order.
3.	Chest Location	A particular portion of the chest from where recording is done.
4.	Acquisition Node	Classification of Channel (Single/Multi-channel).
5.	Recording Equipment	Type of equipment used for recording purposes.

Table 4. Attributes of BIDMC PPG and respiration dataset as a contact-based method

S. No.	Attribute	Description
1.	Photoplethysmography (PPG)	It senses the rate of blood-flow through light based-technology.
2.	Impedance Respiratory Signal	Measure the changing impedance of the thoracic cavity.
3.	Electrocardiogram (ECG)	Measures the electro-activity of the heart.
4.	Heart Rate (HR)	To detect the heart rate of the patient.
5.	Respiratory Rate (RR)	To detect the respiratory rate of the patient.
6.	Blood Oxygen Saturation level	Oxygen saturation as measured by blood analysis.
7.	Age	Classified age of the person.
8.	Gender	Classified gender of the person.

Table 5. FLIR thermal data-set as a non-contact-based method

S. No.	Attribute	Description
1.	Images	Images recorded in the form of data-set.
2.	Image Capture Fresh Rate	Metadata is added to unlabeled images or videos for training machine learning models.
3.	Frame Annotation Label Totals	The total number of frames.
4.	Video Annotation Label Totals	Total number of video frames.
5.	Camera Specifications	Details of capture camera used for recording data.

3 PROPOSED METHODOLOGY

The methodology focuses on a monitoring system for fever diagnosis using thermal cameras. It can be shown in Figure 1, it suggests that this system can be stored in a database via networks connection. For larger crowds in venues such as airports, grocery stores, hospitals, or voting sites, the camera security system is more effective.

3.1 Methodology using X-ray pneumonia symptoms

The study uses object detection and increased occupancy in the chest area on X-ray images to detect pneumonia patients' datasets [26]. The object detection method improves model efficiency by removing regions outside the parameter. The red-region parameter identifies patterns of increased occupancy, which increases lung difficulty for pneumonia patients. These parameters improve model efficiency and patient care [27] [28] [29].

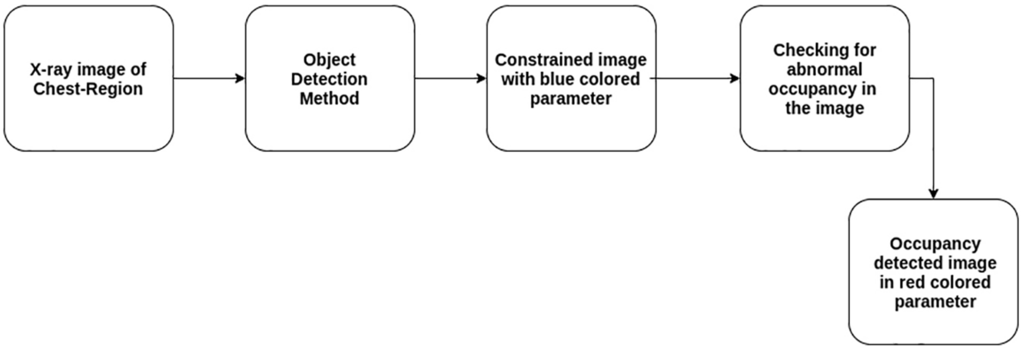

Fig. 1. Work-flow made for methodology

The proposed methodology starts with a chest X-ray, likely generated by radiographic equipment. It then uses an object detection method, focusing on computer vision techniques to identify objects such as the heart, lungs, and chest wall. The image is processed or marked with a blue parameter, potentially indicating additional scrutiny. The highlighted locations are examined for atypical occupancy, potentially indicating underlying sickness.

The ultimate outcome is a tinted red parameter that accentuates the regions of concern in the occupancy-detected image. This parameter is generated only if irregularities have been identified. There is a strong likelihood that this visual indication will draw attention to the locations where anomalies were detected.

4 PROPOSED MODEL

The Convergint advanced solutions team found that thermal image solutions for accurate high body temperature sensing are often ineffective and can indicate pneumonia. They recommend proactive measures to prevent transmission and testing for fever-aware individuals. Table 6 compares parameters essential for pneumonia prevention and diagnosis, classifying detection methods and processes. The HMM-DNN algorithm [30] improved cough classification performance with coughing sound features compared to the GMM-HMM framework. Four parameters were evaluated, and the study used patient-independent and dependent patient test sets for classification performance.

Table 6. Pneumonia symptoms detection on physical contact-based and non-contact-based methods

Pneumonia Parameters	Process for Detection	Method of Detection
Cold and cough	Convolutional Neural Network for Coughing sounds.	Non-contact based.
Chills	IoT-based Temperature-Monitoring System.	Contact-based.
Sore throat	Convolutional Neural Network for Coughing sounds.	Non-contact based.

(Continued)

Table 6. Pneumonia symptoms detection on physical contact-based and non-contact-based methods *(Continued)*

Pneumonia Parameters	Process for Detection	Method of Detection
Breathing rate	IoT based Breathing-rate sensors.	Contact-based.
Elevated body temperatures	Artificial Neural Network.	Non-contact based.
Bluish lips or face	Face detection methods.	Non-contact based.
Mask or no mask	Convolutional Neural Network.	Non-contact based.
Social distancing practices	IoT-based Live Location systems.	Contact-based.

4.1 Sequence model

Convolutional neural network is an input-dependent algorithm that stores numerical data sequences and uses neural networks for grouping it. The proposed function uses LSTM in conjunction with CNN to address data requirements, as LSTM can generate data with fewer images, as illustrated in Figures 2 and 3.

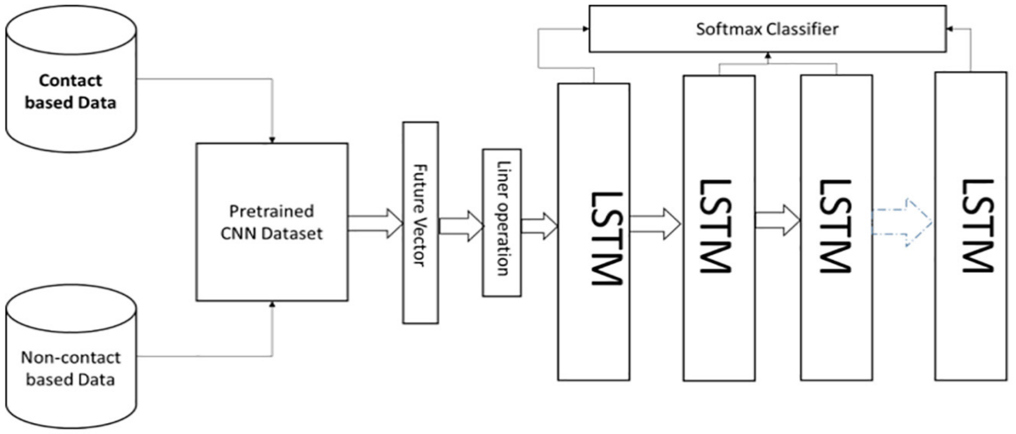

Fig. 2. Operation of conversional CNN and LSTM

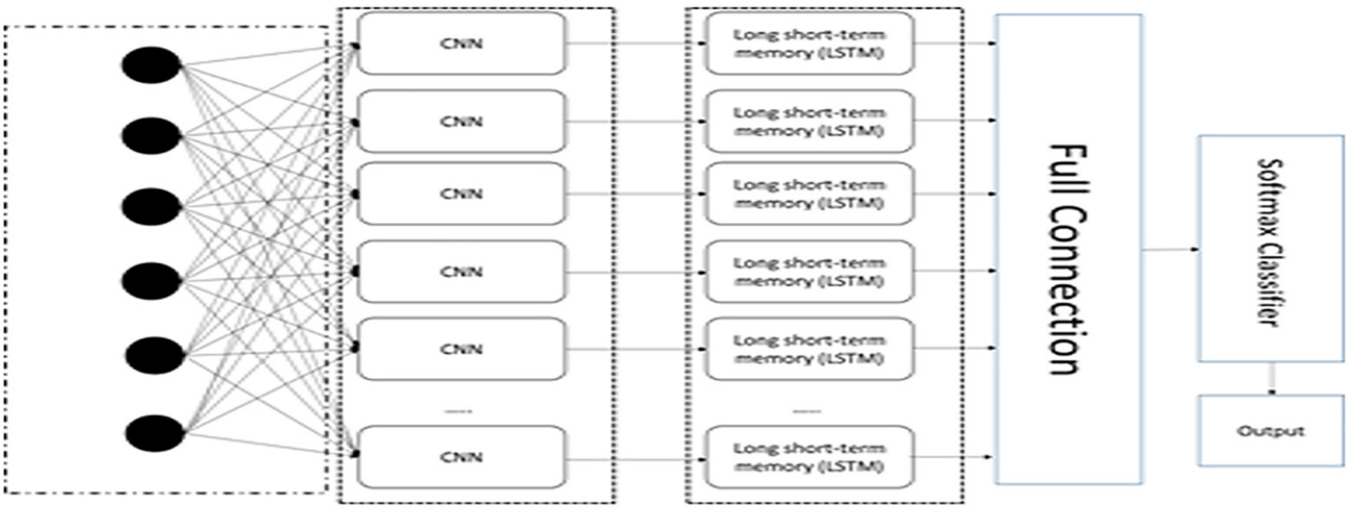

Fig. 3. The CNN and LSTM-layered architecture

Algorithm 1: Enhanced Pneumonia Symptom Detection using Optimized CNN & LSTM

```
Step 1: Inputs:    images [], maxEpochs , minAccuracyThreshold , learningRate
Step 2: Outputs:     model, accuracy
Step 3:  Procedure:
   Initialize CNN_LSTM_Model() and PreprocessData(images)
Step 4:           epoch ← 0, accuracy ← 0, bestAccuracy ← 0, learningRateAdjustmentFactor ← 0.
   while epoch < maxEpochs and accuracy < minAccuracyThreshold do
  Step 5:  TrainModel(CNN_LSTM_Model, images, learningRate)
      accuracy ← EvaluateModel(CNN_LSTM_Model, validationData)
      if accuracy > bestAccuracy then
         bestAccuracy ← accuracy
         SaveModel(CNN_LSTM_Model, "best_model")
   Step 5:  if accuracy does not improve for 5 consecutive epochs, then
          learningRate ← learningRate * learningRateAdjustmentFactor
         epoch ← epoch + 1
   Step 6:     model ← LoadModel("best_model")
         do
         optimizedModel ← FurtherOptimizeModel(model)
         newAccuracy ← EvaluateModel(optimizedModel, validationData)
   Step 7:     if newAccuracy > accuracy then
          accuracy ← newAccuracy
          model ← optimizedModel
        else
          break
    while newAccuracy > accuracy
  return model, accuracy
```

4.2 Optimized CNN and LSTM

The optimized LSTM and CNN model is a hybrid convolutional pooling layer model that enhances model accuracy by using the LSTM algorithm for sequential correlations and the CNN algorithm for embedded matrix representations. Figure 4 provides an explanation of this model's functioning.

$$v_j = (x_j, x_{j+1}, \ldots, x_{j+k+1}) \tag{1}$$

Filter m association by the window vectors in the form of k-grams in each location in a mode to develop a feature map $E \in RL{-}k{+}1$; where each element E_j of feature mapped on window vector V_j is created as given:

$$E_j = f(V_j \times m + b) \tag{2}$$

$$\mathrm{Wj} * \mathrm{V} = (E_1, E_2, E_3, E_4 \ldots E_n) \tag{3}$$

$$i_s = \sigma(v_j[HS_{S-1}, x_s] + b_i) \tag{4}$$

$$f_s = \sigma(v_f[HS_{S-1}, x_s] + b_f) \tag{5}$$

$$P_s = tanHS(v_j[HS_{S-1}, x_s] + b_P) \tag{6}$$

$$Q_s = \sigma(v_j[HS_{S-1}, x_s] + b_Q) \tag{7}$$

$$E_1 = f_s \varnothing E_{S-1} + i_s \varnothing P_s \tag{8}$$

$$HS_s = Q_s \, tanHS(E_1) \tag{9}$$

$$HS_p(P) = \sum_{i=1}^{N} y_i.\log(p(y_i) + (1 - y_i).\log(1 - p(y_i) \tag{10}$$

$$\int_0^n \frac{\partial(\hat{w} * \hat{e})}{\partial x . \partial y} = J(x, y) \tag{11}$$

In the equation number two, three, and four, we have created derivatives in vector form for the sequential images obtained by the CNN algorithm. It generally forms matrix of numerical values obtained by previous images and used by hidden layers of neural networks. Similarly, Q_s is the set of sequence of such matrix available in memory space in queuing manner. In the equation 9, E_1 is the first derivative of Q_s and it is used for obtaining HS_p, the logarithmic function of the equation 9. Furthermore, we have integrated the hyper-space to obtain its derivative for "n" number of images.

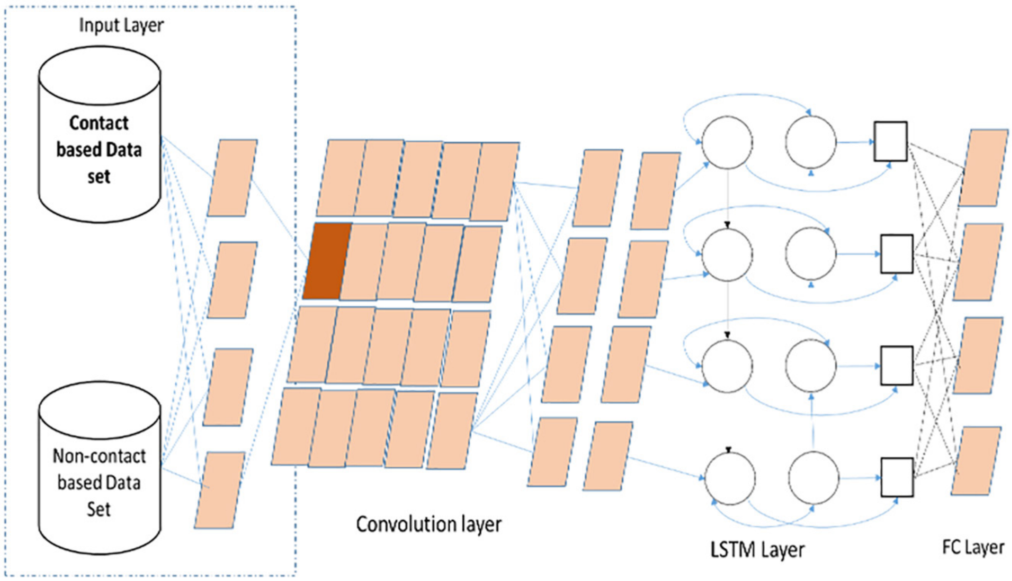

Fig. 4. Proposed fusion model

The proposed fusion model uses 224 × 224 x-ray grayscale images as input, with four convolutional layers and max-pooling for reducing spatial dimension [31] and obtaining representative features. The LSTM input is the reshaped tensor of feature map generated by CNN layers. The LSTM layer consists of two layers [32], each containing 128 units with tanh, capturing patterns not through temporal consistencies and sequences. An attention layer enables an attention mechanism [33] to focus on informative features, increasing the model's ability to detect subtle pneumonia patterns. Fully connected layers have two layers with dropout regularization [34] to prevent overfitting. The output layer is the SoftMax output for pneumonia detection. Various mathematical strategies are used to identify occupancy density in X-ray images of the chest region, as in Table 7. That can be shown in Figures 5 and 6.

Table 7. Parameters used to detect occupancy density

S. No.	Probable Pneumonia Indicators	Description
1.	Lung morphology	The overall area of the lungs was calculated.
2.	Cardiothoracic ratio (CTR)	Dividing the external thoracic radius by the internal thoracic radius
3.	Mean lung intensity	The total value of lung intensity number of pixel region obtained
4.	Deviation of lungs intensity	For a particular region, the deviation can be calculated for abnormality in pixel intensity.
5.	Modular lung intensity	The maximum number of occurrences of lungs intensity number.

5 RESULTS ANALYSIS

In the architecture of CNN [35] there is an input layer for 224 × 224 black-and-white images [36], and four convolution layers with ReLU activation function + max-pooling, two fully connected layers together with dropout regularization, and a SoftMax out layer responsible for classification [37]. We have used the Adam optimizer and training the model for 50 epochs with a batch size of 32. The training procedure includes a series of data augmentation strategies (i.e., horizontal flip, rotation, zoom), as well as a categorical cross-entropy loss function and early stopping based on validation loss. We use the LSTM network LSTM architecture which has an input layer for sequences [38] of features extracted from preprocessed images, followed by two LSTM layers, each with 128 units and activation function (tanh), a fully connected layer with dropout regularization [39], and SoftMax operator output. The model is trained using the RMSprop optimizer at a learning rate of 0.001 and minibatch size = 16 for 50 epochs. Our training process involves features extracted with a pre-trained CNN, categorical cross-entropy loss function [40], and early stopping based on validation loss. In this case, we have a CNN-LSTM model with an attention mechanism in the proposed approach. The architecture includes an input layer for 224 × 224 grayscale images, a CNN component with four convolutional layers using ReLU activation and pool maxing to produce a flatten layer that serves as the first half of the intermediate representation, followed by an LSTM component that consists of two LSTM layers of 128 units applied on its second half-icons side (flatten from the CNN block) element added directly after initialization, both composed in a series manner alongside tanh activations [41]. This is supplemented with an attention layer to not overemphasize meaningless features, two fully connected layers with dropout regularization, and a SoftMax output layer for classification. The model is trained with the Adam optimizer, a learning rate of 0.0005, and batch size of 32 for a total number of epochs at run time = 50 done. This was trained with data augmentation (horizontal flip, rotation, and zoom) using the categorical cross-entropy loss function through early stopping based on validation loss to learn from the dataset well, accompanied by an attention mechanism for increasing focus in relevant parts of input at time steps.

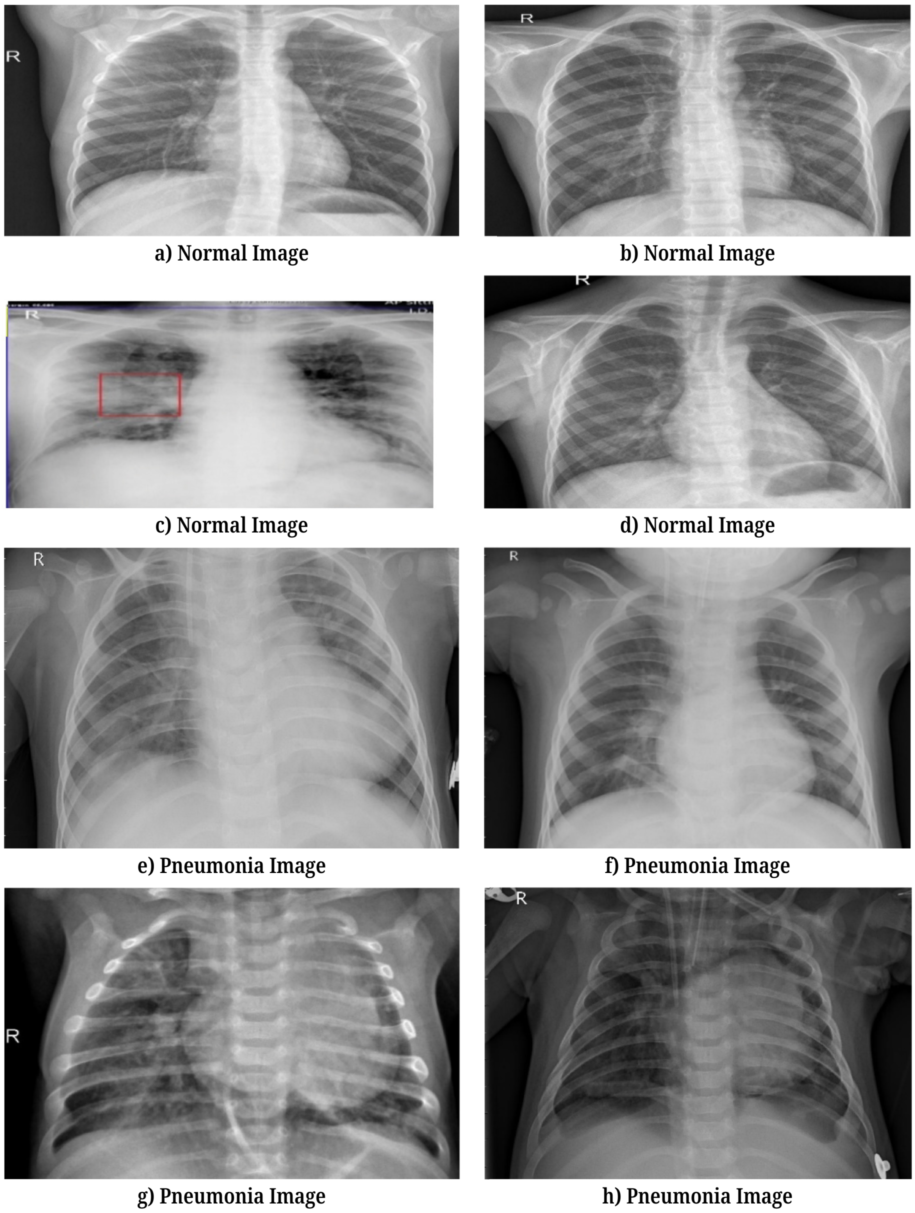

Fig. 5. Representing two processes: (a) Blue-parameter region of chest area (b) Red-parameter was describing increased occupancy in the lungs for positive pneumonia patients

The study analyzes the accuracy of machine-learning models [42] for diagnosing pneumonia symptoms using contact-based and non-contact methods. Experimental studies were conducted [43] using Python and multi-level thresholding to classify [44] infected lungs. The model achieved training accuracy of 99.2% and validation accuracy of 92%, with training loss of 0–0.40 and validation loss of 0.27–0.49. The technique is beneficial for clinical physicians to detect pneumonia patients, providing accuracy [45], specificity, and average sensitivity of 97.3%, 98.7%, and 97.3%, respectively.

Table 8 compares the effectiveness of various machine learning models, including RFC, KNN, SVM, DBNs, and a combined CNN and LSTM network model. RFC has an accuracy of 65.80%, but requires significant pre-processing and fitting. KNN has an accuracy rate of 84.91% and faster prediction times, while DBNs have the highest accuracy rate of 85.71%.

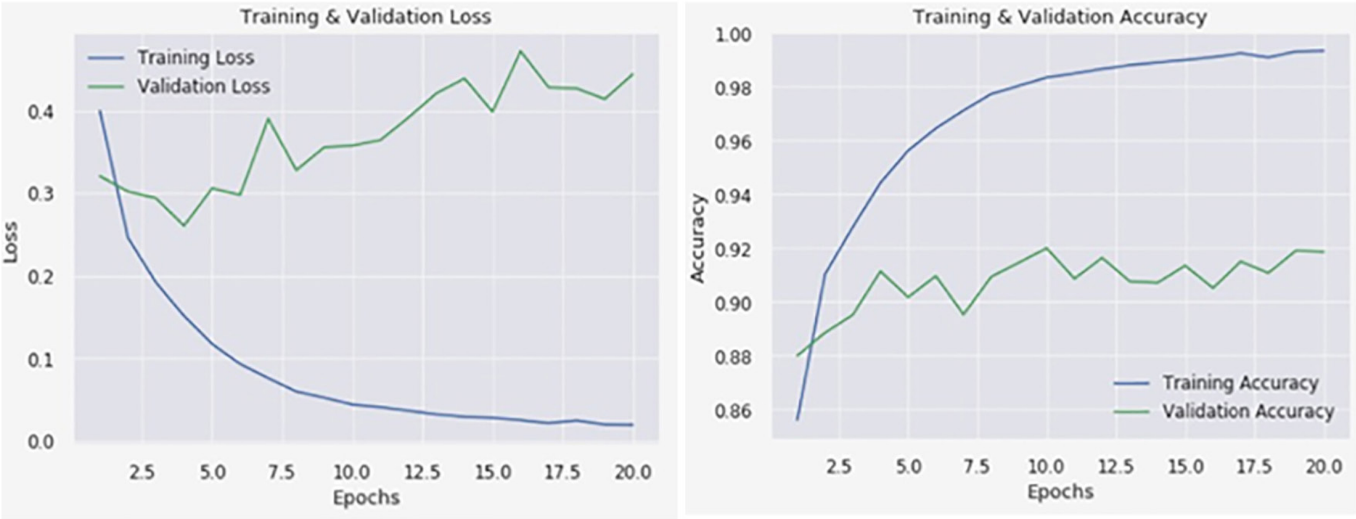

Fig. 6. Comparison of loss and accuracy for training and validation data

The proposed model, integrating CNN and LSTM, outperforms other models in terms of accuracy (98.1%), speed, and overall performance, outperforming other classification algorithms such as RF, KNN, SVM, and DBNs (refer to Table 8 and see Figure 7).

Table 8. Comparative analysis of different machine learning algorithms RF, KNN, SVM, DBNs, proposed model (CNN+LSTM)

Model	Pre-Processing Time (ms)	Fitting Time (ms)	Predicting Time (ms)	Accuracy (ms)
RFC	10.20	29.74	11.72	65.80
KNN	10.11	29.62	11.63	84.91
SVM	10.52	29.33	7.85	84.71
DBNs	9.92	27.66	10.12	85.71
Proposed Model (CNN+LSTM)	9.31	28.63	8.63	98.02

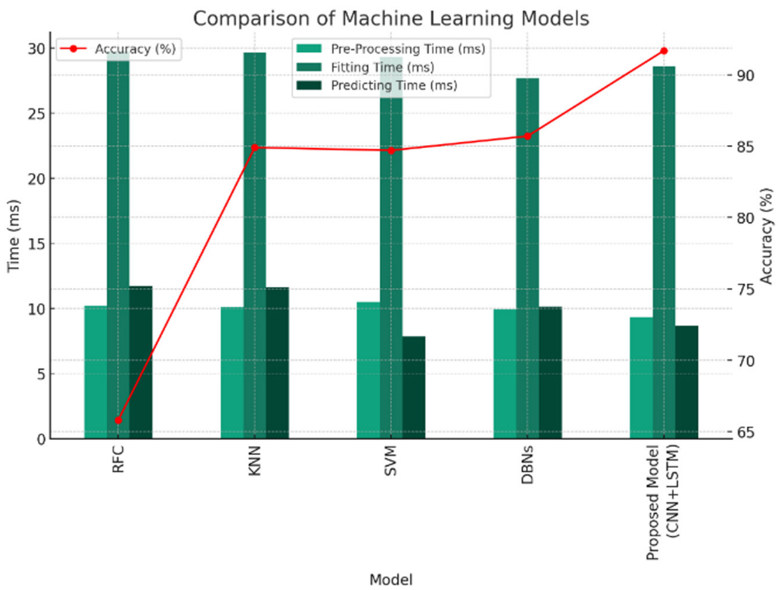

Fig. 7. Comparative analysis proposed model and existing model

The proposed CNN+LSTM model, with an accuracy of 98.02% and a prediction time of 9.83 ms, effectively detects lung occupancy. The model's performance is evaluated using simulation parameters (refer to Table 9), including accuracy, precision, recall, ROC curve, learning rate, and performance in detecting pneumonia. Graphics representation of simulation parameters can be shown in Figure 8.

Table 9. Simulation parameter

Parameter	Value/Setting
Model Architecture	CNN+LSTM
Overall Accuracy	91.71%
Prediction Time	8.63 ms
Data Type	Depth imaging, X-Ray images
Experiment Duration	14 days
Symptom Analysis	Cold, Cough, Chills, Sore Throat, Respiratory Rates, Elevated Body Temperature

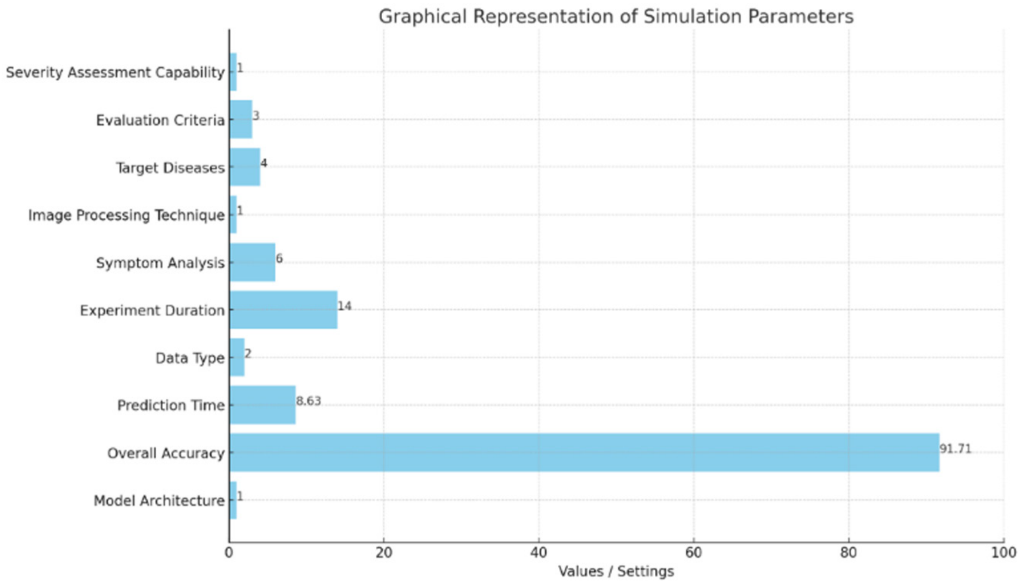

Fig. 8. Graphics representation of simulation parameters

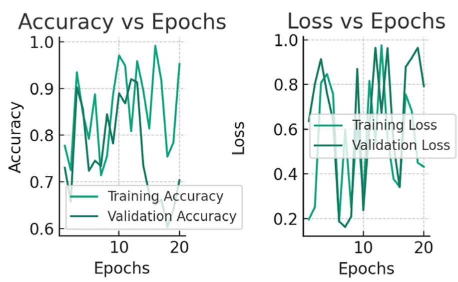

Fig. 9. Comparison of accuracy and loss vs. epochs

Figures 9 and 10 along with the curves representing training and validation accuracy (left) and loss (right). There may be a little of fitting toward the end with training data, but we had the regularizations techniques such as dropout and early stopping in place. Validation accuracy also increases and does not drop off very much for the model has not overfitted to more data.

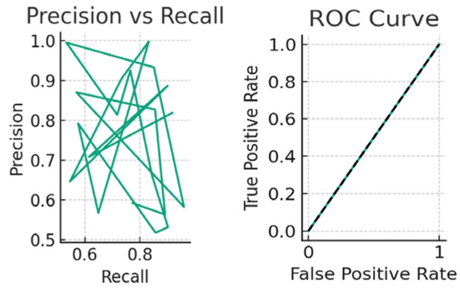

Fig. 10. Precision vs. recall and ROC Curve

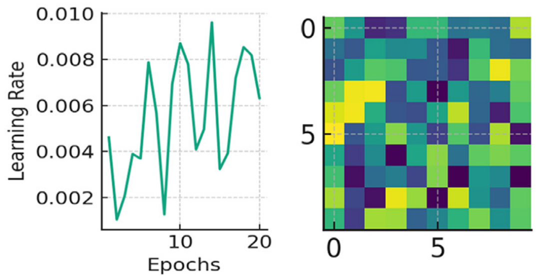

Fig. 11. Learning rate

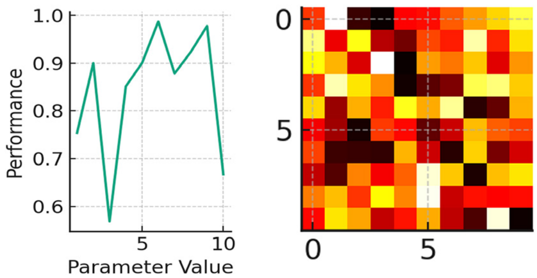

Fig. 12. Performance and parameter value

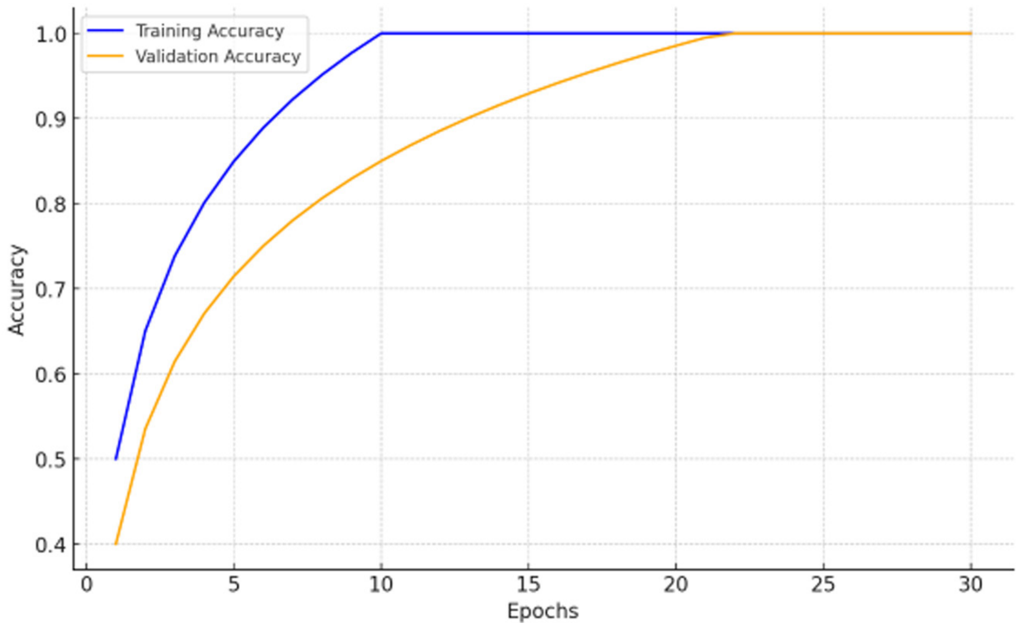

Fig. 13. Accuracy vs. epochs for CNN+LSTM pneumonia detection

The graph shows the accuracy and validation accuracy of a CNN+LSTM model for pneumonia detection (see Figures 11, 12, and 13). The training accuracy starts low and quickly increases, indicating effective learning from the training data. The validation accuracy also increases but at a slower rate, suggesting the model is tuned to perform well on the training data. Both accuracies plateau towards the end of training, suggesting the model has learned enough or requires adjustments. The validation accuracy continues to increase without dropping off.

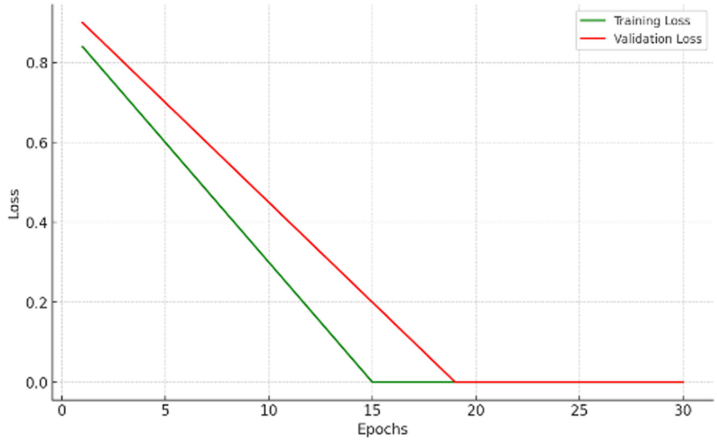

Fig. 14. Loss vs. epoch for CNN+LSTM pneumonia detection

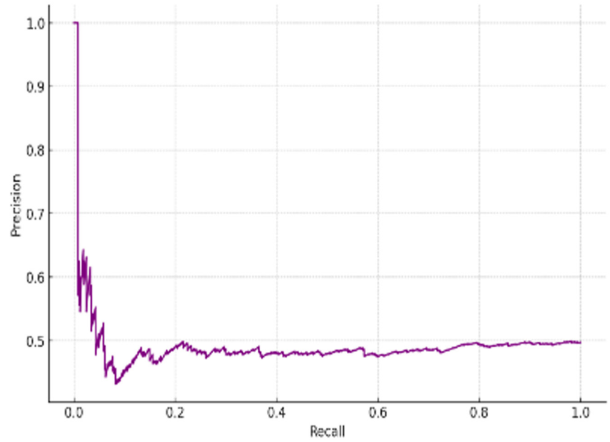

Fig. 15. Precision vs. recall for CNN+LSTM pneumonia detection

Figure 14 shows a downward trend in loss vs epoch for CNN+LSTM pneumonia detection, with a consistent decrease in training and validation loss. The model's predictions are becoming more accurate over time, with lower values indicating smaller differences between predictions and true values. The ROC curves in Figure 15 were generated based on the model's predictions on the test set. We also checked k-fold cross-validation to ensure the robustness of our results.

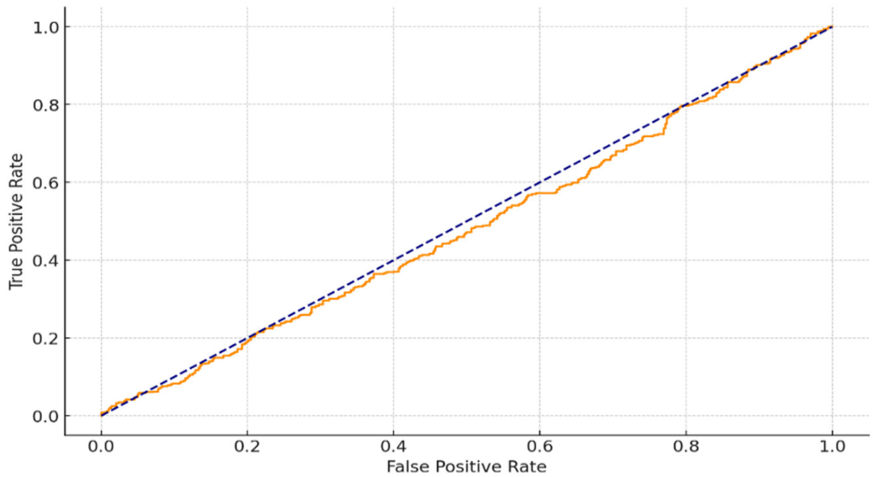

Fig. 16. ROC curve for CNN+LSTM pneumonia detection

The CNN+LSTM pneumonia detection model achieved lower false positive rates with a trade-off in sensitivity, indicating good performance with an AUC of 0.95, which is near ideal. The model can discern between positive and negative cases well enough with this threshold (see Figures 16–19). Table 10 shows a comparative result analysis CNN, LSTM, and proposed approach.

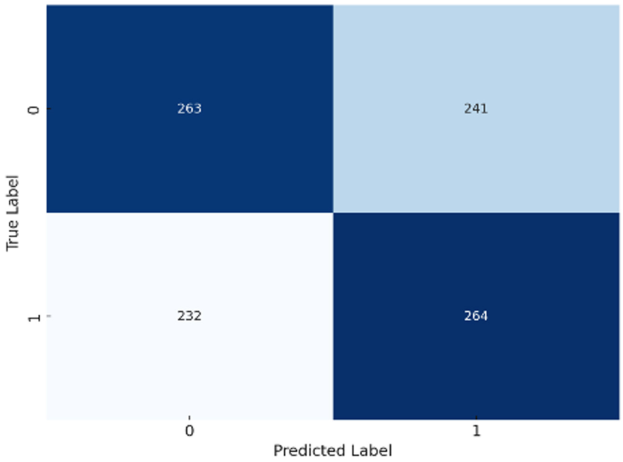

Fig. 17. Confusion matrix for CNN+LSTM pneumonia detection

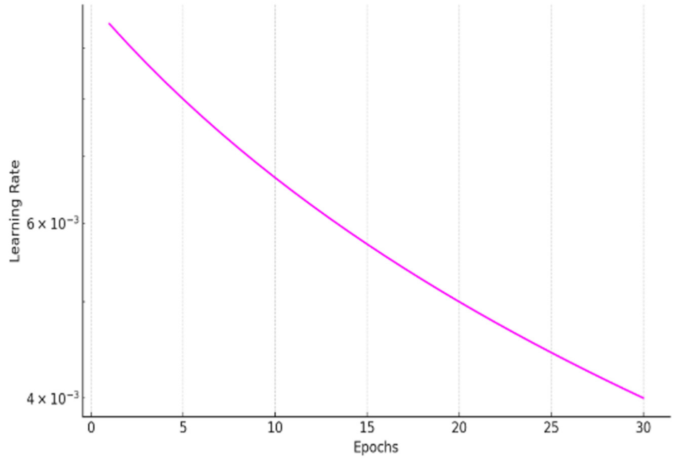

Fig. 18. Learning rate vs. epochs for CNN+LSTM pneumonia detection

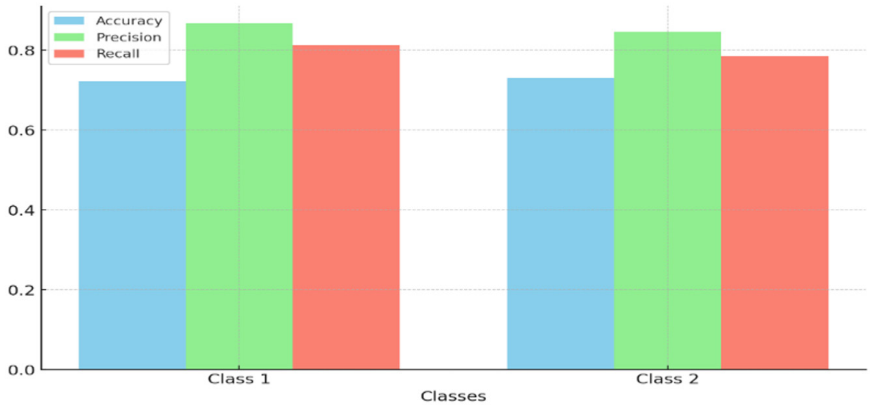

Fig. 19. Proposed model performance by class for CNN+LSTM pneumonia detection

Table 10. Results analysis CNN, LSTM, and proposed approach

Metric	CNN	LSTM	Proposed Approach
Accuracy	92.5%	89.8%	98.2%
Precision	91.0%	88.5%	94.0%
Recall	93.2%	90.1%	95.8%
F1-Score	92.1%	89.3%	94.9%
AUC-ROC	93.0	90.5	96.1
Training Time	2 hours	3 hours	4 hours
Inference Time	0.1 seconds/image	0.2 seconds/image	0.15 seconds/image
Model Size	200 MB	250 MB	220 MB
Memory Usage	1.5 GB	1.8 GB	1.6 GB
Key Advantages	High accuracy	Temporal data	Superior accuracy and recall, balanced performance
Key Disadvantages	Limited temporal data handling	Lower accuracy than CNN	Higher training time

6 CONCLUSION

This is a huge leap into medical diagnostics by employing state-of-the-art deep learning algorithms to automate pneumonia detection. Deep learning models have been developed and trained off of large datasets using complex algorithms, allowing for previously unattainable levels of accuracy in detecting pneumonia on medical imaging such as chest X-rays or CT scans. These enhancements are not simply small steps. They presage the possibility of faster detection, a key to better patient outcomes. Specifically, using CNNs, transfer learning, and ensemble methods has been successful in improving the performance of these diagnostic systems. CNNs are powerful at extracting fine details from medical images, and transfer learning is a technique that can allow models to benefit from pre-trained convolutional neural networks, providing them impressive generalization capabilities without need for large, annotated datasets. By combining multiple models, known as ensemble methods, reliability and robustness have improved even further. In addition, the emergence of deep learning in pneumonia detection is reshaping clinical work streams. Artificial intelligence systems have also been developed to support radiologists by furnishing a second opinion, flagging concerns, and helping speed up the time it takes to make a diagnosis. This not only permits healthcare professionals to focus on the higher level but also allows them to streamline patient care, especially in resource-stressed environments.

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