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Deep Learning-Based Prediction of Lung Disease: A Comprehensive Analysis and Proposed Methodology

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ABSTRACT- Early diagnosis of lung diseases is very essential in ensuring fewer deaths and better treatment to the patient. One of the most widely applied techniques of diagnosing lung conditions is the chest X-ray, which can be occasionally slow to interpret manually and differs according to the experience of the medical practitioner. To overcome these difficulties, this study will offer an Intelligent Lung Disease Prediction System where a hybrid deep learning method will be applied to the analysis of chest X-ray images using Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The model is formed to differentiate between the X-ray images by categorizing them into three different classes, namely, Normal, Viral Pneumonia, and Lung Opacity. To obtain the spatial features effectively out of the images, they utilize a pre-trained ResNet50 model but, to extract more relations between the extracted features in order to enhance the classification performance, they make use of the LSTM layer. To make the system more intuitive and transparent, the model is combined with the Grad-CAM visualization that brings out the particular parts of the X-ray image that affect the predictions of the model. This assists the users to know where the model is focusing on towards the detection of possible abnormalities. The trained model is deployed as a web application written in Flask, where users upload images of their chest X-rays and receive real-time predictions with visual explanations. The site also incorporates facilitating features like simplistic health tips and the co-opetition on whether to visit the doctor, which make it more practical. On the whole, this system shows that deep learning methods can be utilized to aid in early detection of lung diseases and increase the availability of initial medical examinations.

KEYWORDS: Lung Disease Detection, Chest X-ray Classification, Deep Learning, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), ResNet50, Medical Image Analysis, Hybrid Deep Learning Model, Heatmap Visualization, Computer-Aided Diagnosis (CAD), Flask Web Application, Artificial Intelligence in Healthcare.

I. INTRODUCTION

Lung problems like viral pneumonia and lung opacity can get dangerous fast if you don't catch them early. They mess with your breathing, and that's nothing to take lightly. Doctors usually turn to chest X-rays because they're quick and don't cost a fortune. But here's the thing: checking these X-rays is all up to the radiologist's expertise. If you're in a busy hospital, they've got a pile of images to go through, and it takes ages. Sometimes people can look at the thing and see it differently which can lead to delayed or inconsistent diagnoses.

Artificial Intelligence and deep learning techniques are getting better fast. Because of this automated medical image analysis is becoming very popular. Convolutional Neural Networks are often used to classify images because they're good at finding important features in images. Traditional Convolutional Neural Networks may not be able to fully understand the relationships between the features they find. To fix this problem people are trying out approaches that combine Convolutional Neural Networks with Long Short-Term Memory networks to improve performance.

In this study we made a Lung Disease Prediction System that uses a Convolutional Neural Network and Long Short-Term Memory architecture to classify chest X-ray images into three categories: Normal, Viral Pneumonia and Lung Opacity. We used a -trained ResNet50 model to extract features from the images and the Long Short-Term Memory layer helps us understand the relationships between these features. We built a web application using Flask that lets users upload chest X-ray images and get predictions away. The system also gives users health advice. Suggests that they consult a doctor, which shows how Artificial Intelligence can help us detect lung diseases early. The Lung Disease Prediction System is a tool that can help people with Lung diseases, like Viral Pneumonia and Lung Opacity.

II. LITERATURE SURVEY

Deep learning has made a substantial impact on the prediction of lung disease through the use of audio and video images, and the classification of breathing sounds has drawn on a number of different technologies over the years. CNNs and LSTMs are two technologies that have been frequently used for the purpose of classifying breathing sounds. A model that used both CNN and LSTM to form a dual channel CNN-LSTM classification system has been proposed by Y. Zhang [1], This model utilized MFCC-based spectrograms as input feature data.

Similarly, S. D. Santumon [2] a hybrid CNN - LSTM framework was developed to perform automated lung sound analysis, and the use of deep feature extraction in combination with sequential learning allowed the system to perform significantly better at distinguishing between normal lung sounds and abnormal lung sounds compared to other classification approaches.

An automated lung sound classification approach [3], CNN-LSTM model using spectrogram-like feature inputs processed with Convolutional layers prior to using LSTM units as a way to learn temporal dependencies of the respiratory datasets. This resulted in a high accuracy for classifying example respiratory data.

P. Zhang [4], a comparative study between CNN-LSTM, and CNN-BiLSTM architectures was conducted for pulmonary audio classification. The results indicated that hybrid CNN-BiLSTM models outperformed standalone CNN and LSTM models in detecting COPD and pneumonia.

A hybrid CNN-LSTM architecture for lung cancer detection from chest X-ray images was introduced by Pradhan et al. [5]. The CNN extracted high-level image features, while the LSTM modelled feature dependencies, improving classification robustness.

Apart from audio-based systems, deep learning methods using chest X-ray and CT images have shown promising results.

M. Jasmine Pemeena et al. [6] proposed for detecting pneumonia, tuberculosis, and lung cancer from radiographic images, demonstrating high diagnostic performance.

A deep learning framework for pulmonary infection detection was presented by K. Hammoudi [7], focusing on viral pneumonia and COVID-19 classification using chest X-ray datasets.

A multi-class deep learning architecture combining CNN with pre-trained models such as ResNet and DenseNet was introduced by Al-Sheikh [8] for classifying multiple lung diseases.

S. Shahzad [9] built a deep ensemble CNN model for chest X-ray disease detection. By bringing together several CNN architectures, they boosted accuracy for classifying tuberculosis and other lung diseases.

M. Patel et al. [10] tried a similar strategy they used a deep ensemble learning approach and combined fixed deep features from different CNN models. This fusion made multi-class lung disease diagnosis more reliable.

Alshanketi et al. [11], studied a deep dive into how various deep learning methods handle pneumonia detection. They compared performance metrics and looked at how results changed depending on the dataset.

S. Sarker et al. [12] studied used transfer learning with a mix of datasets to spot lung diseases. That helped the model perform better, even when faced with new, different data.

Ifty et al. [13] looked at explainable AI for spotting different lung diseases. They used CNN-based models and added visualization tools so people could actually see and understand what the AI was doing.

T. Sanida et al.[14], designed a lightweight CNN that diagnoses lung diseases fast and doesn't need much computing power, all while keeping its accuracy solid.

Lately, researchers have started experimenting with hybrid transformer-CNN models. X. Fu et al.[15], they came up with a new explainable hybrid transformer that mixes convolutional feature extraction and attention mechanisms to boost classification results.

T. Rahman et al.[16], looked into transfer learning with deep CNNs like ResNet and DenseNet for pneumonia detection. They showed that pre-trained models really work well for medical imaging.

They looked at several CNN models for automated pneumonia classification in [17] and showed how the depth and design of a model can really change results.

A. Ahsan et al. [18] highlights the role of deep learning in detecting network anomalies in IoT-integrated cloud environments, focusing on optimization strategies to handle challenges like scalability, heterogeneity, and real-time detection

A. Ahsan [19], reviewed hybrid transfer and ensemble approaches for lung disease classification, pointing out that using multiple models helps make predictions stronger and more reliable.

In the below Table 1 summarizes the existing methodologies used for lung disease detection along with their techniques and performance.

Table 1: Existing methodologies used for lung disease detection

S.No	Method	Architecture Used	Data Type	Limitation
1	CNN-based Classification	CNN (VGG, ResNet, DenseNet)	Chest X-ray	No sequential feature modeling
2	Transfer Learning Approach	Pre-trained CNN	Chest X-ray	Dataset dependency, overfitting risk
3	Ensemble Deep Learning	Multiple CNN Models	Chest X-ray	High computational complexity
4	CNN–LSTM for Respiratory Analysis	CNN + LSTM	Lung Sound Signals	Applied mainly to audio data
5	Transformer-based Models	Vision Transformer	X-ray / CT Images	Requires large-scale datasets
6	CNN with Activation Maps	CNN + Heatmap	Chest X-ray	Limited localization accuracy

III. PROPOSED METHODOLOGY

The proposed study involves coming up with a hybrid deep learning approach of automated classification of lung diseases using the aid of the chest X-ray images. It is a convolutional neural network (CNN) of ResNet structure and Long Short-Term Memory (LSTM) network. The CNN can only extract significant spatial features of the X-ray images; hence the LSTM can create deeper relationships between the features. These hybrid systems are capable of adding to the quality of the classifications of multi-classes compared to the traditional CNN-only models. The overall workflow is made up of image preprocessing, feature extraction, sequential feature learning, classification, evaluat3*ion, Grad-CAM visualization and web deployment. In the below Table 2, we present the performance comparison between the proposed model and existing models, showing improvements in accuracy and other evaluation metrics

A. Image Preprocessing

The dimensions of all X-ray of the chest are resized to 224 x 224 x 3 to ensure that the size of the input is equal. Normalization of pixel values to [0,1] range is carried out so as to provide stability during the training. The dataset is then stratified to split into training and testing sample, having all of the three classes represented sufficiently; in other words, normal, viral pneumonia, and lung opacity.

B. CNN Feature Extraction.

A ResNet architecture performs extraction of spatial features of the images. The network obtains considerable lung patterns containing the variations in texture, the lung limits, and the regions of opacities. ResNet is a learning technique which entails a residual learning which is formulated as:

$$H(x)=F(x)+x$$

Where x represents the input, F(x) is the residual mapping, and H (x) is the output. The convolutional layers are followed by Global Average Pooling (GAP) which converts the feature maps to a small feature vector.

C. LSTM-Based Feature Learning

The resulting feature is converted into a reshaped form and fed to an LSTM layer of 128 units. Despite the fact that LSTM is typically used with sequential data, it helps to realize more significant dependencies between the spatial representations that are offered by the CNN. This helps to increase the model in selecting fine disease patterns.

D. Classification Layer

The smooth appearances are followed by the Dense layer with ReLu activation and a Dropout layer (0.5) so as to reduce overfitting. The final Softmax layer gives the value of the probability of each of the three classes and the most likely one is selected as the predicted category.

E. Model Evaluation

The model is evaluated using accuracy, precision, recall, F1-score and analysis of the confusion matrix. The correctness of the system was 82 considering all the three classes.

Table 2: Performance comparison between the proposed model and existing models

Approach	CNN Backbone	LSTM Usage	Feature Flow	Accuracy (%)
CNN-only Model	VGG16	Not Used	CNN → Dense → Softmax	78.4 %
Transfer Learning CNN	DenseNet121	Not Used	Pre-trained CNN → Softmax	80.2 %
Parallel CNN–LSTM	Custom CNN	Parallel Fusion	CNN + LSTM merged	79.6 %
Ensemble CNN Model	VGG + ResNet	Not Used	Multiple CNN outputs combined	81.0 %
Proposed CNN–LSTM	ResNet (from scratch)	Sequential	**CNN Output → LSTM → Dense → Softmax**	**82.0 %**

F. Visualization Grad-CAM

To increase the interpretability, grad-cam is used in order to generate heatmaps showing areas of the lungs that influence the prediction of the model. The activation of areas infected in the abnormal cases is intense compared to the insignificant amount of activation of normal pictures.

G. Web-Based Deployment

The trained model is used as a web-based Flask application where the user can submit an X-ray image and a real-time prediction can be sent. The system also displays the predicted category of disease as well as the confidence score, Grad-CAM visualization and simple health advice, which makes the solution so real and can be used in the actually existing world. In Figure 1, we illustrate the overall architecture of the proposed CNN-LSTM model. It shows how the input chest X-ray image is processed through ResNet for feature extraction and then passed to the LSTM layer for sequential learning before final classification.

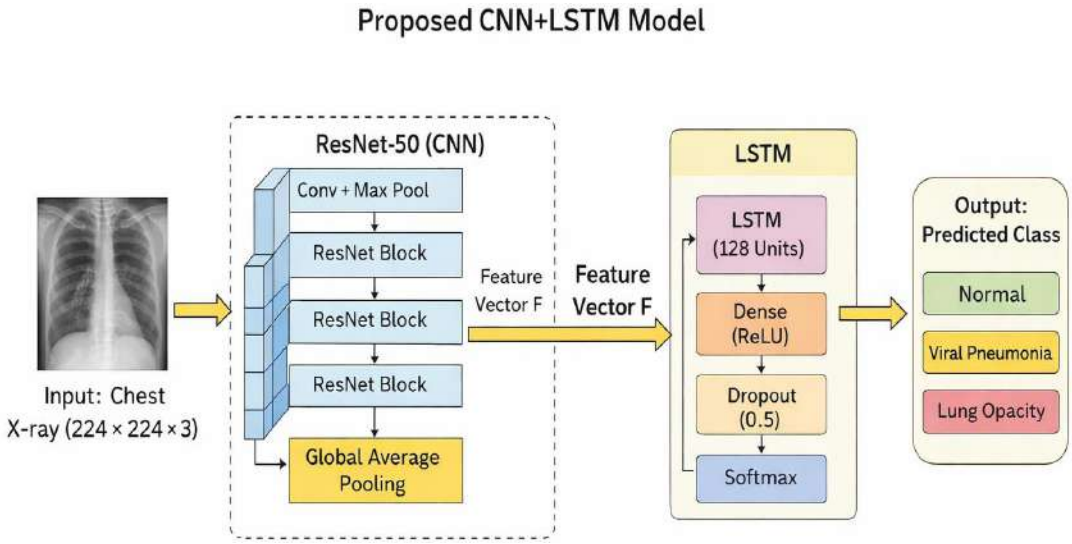

Figure 1: Architecture of the proposed CNN-LSTM model.

IV. RESULT ANALYSIS

The suggested hybrid CNN-LSTM was tested on a stratified train-test split on a chest X-ray dataset, with three classes, namely, Normal, Viral Pneumonia, and Lung Opacity. Accuracy, precision, recall, F1-score, loss analysis and confusion matrix analysis were the measures of performance.

A. Training Performance

The training and validation accuracy curves indicate that there is no major overfitting to the learning curve. The accuracy increased slowly with the epochs as well as the accuracy of validation, meaning that there was good generalization. The values of training and validation loss were also reducing consistently indicating that the model learnt significant features based on the dataset.

B. Classification Performance

The model had general accuracy of 82 percent of the test dataset. Macro-average precision, recall and F1-score were around 0.82, which shows equal performance in all classes. The confusion matrix indicates a high level of detection of Lung Opacity, consistency in classification of the normal ones and slight confusion of Viral Pneumonia with Lung Opacity considering the visual similarity of the two situations. In Figure 2, we are showing the training and validation accuracy and loss curves. It indicates that the model achieves stable learning with minimal over fitting.

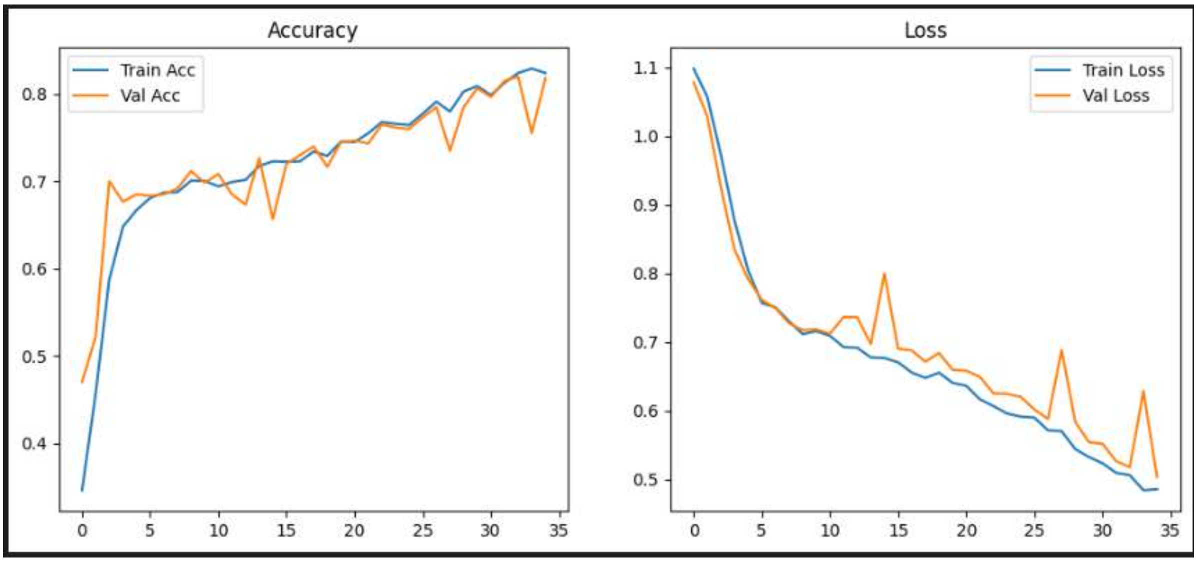

Figure 2: Training and validation accuracy and loss curves

C. Effects of Hybrid Architecture.

Experimental comparisons revealed that CNN-only models only learned spatial features, but no further relational learning occurred, whereas LSTM-only models were weak in learning visual patterns. The CNNLSTM architecture was found to be highly effective in the accuracy of classification and the loss, and inclusion of both models under the same architecture is effective.

D. Grad-CAM Visualization

Predictions were influenced by infected lung regions that were highlighted with the help of grad-CAM. Affected areas were clearly activated in the abnormal cases but little in the normal images. This validates that the model targets the relevant regions of the lungs and better interpretation. In the below Figure 3, we demonstrate the Grad-CAM visualization highlighting infected regions in the lungs that influence the model's predictions

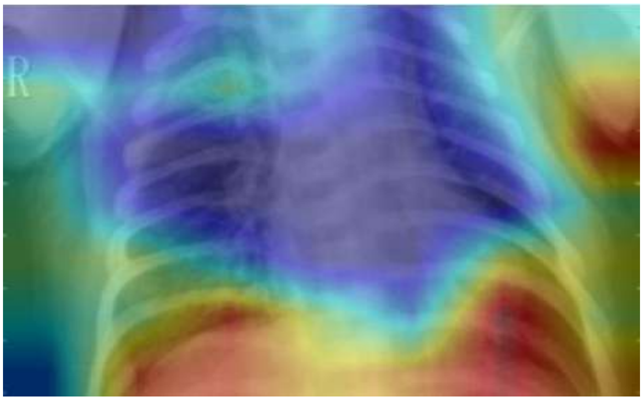

Figure 3: Grad-CAM highlights infected lung regions influencing model predictions

E. Practical Deployment

The flask-based web application that allows uploading X-rays in real-time, capable of generating predictions, confidence scores, visualizing the infected areas, and providing simple health advice was used to deploy the model. This shows the feasibility of the suggested system as a diagnostic aiding program. In the below Figure 4, we are showing the output of the web-based system where users can upload X-ray images and receive predictions along with confidence scores and visual explanations.

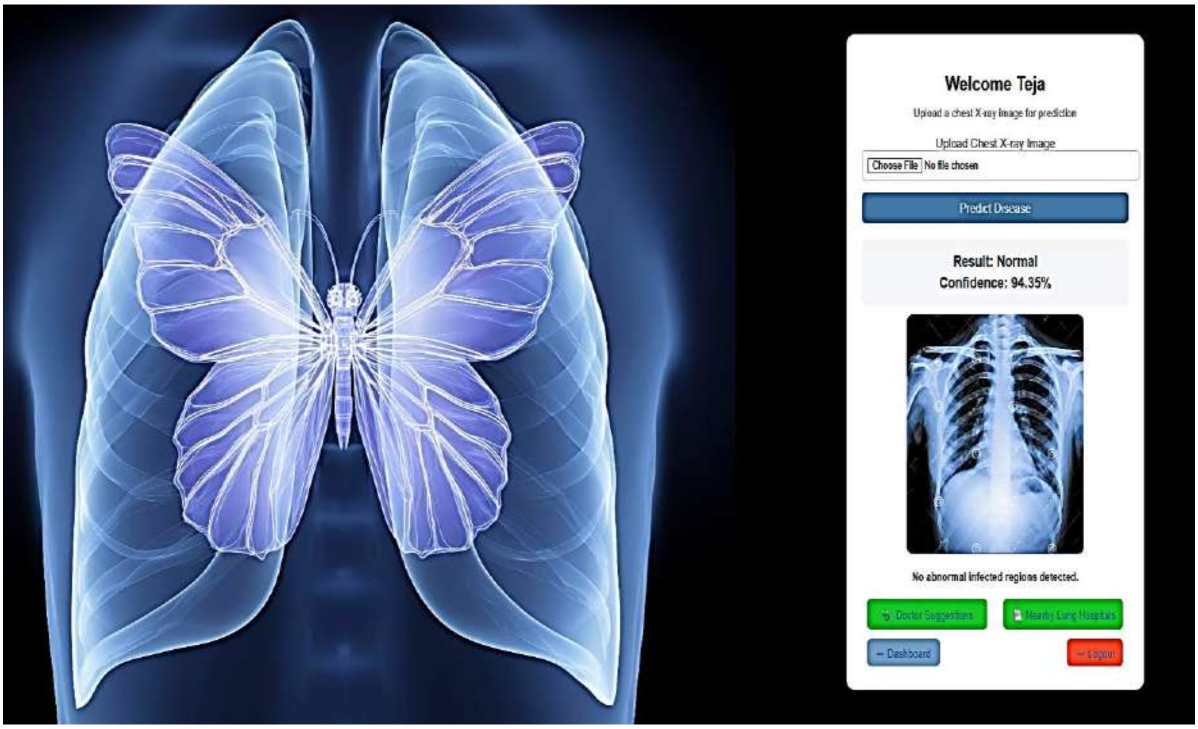

Figure 4: Output of the web-based system

V. DISCUSSION

The results of our experiment show that the hybrid model we made which is a mix of CNN and LSTM is really good at looking at chest X-ray pictures and saying if they are Normal or if they have Viral Pneumonia or if they have Lung Opacity. This model is about 82 percent of the time which means it is very good at finding problems in the lungs.

This model works well because it uses the best parts of both the CNN and the LSTM. The CNN part of the model examines the X-ray images and identifies the key features. Then, the LSTM part analyzes how these features relate to each other, helping the model distinguish between different lung issues.

Looking at the results, we find that the model excels at detecting lung opacity. However, it sometimes confuses viral pneumonia with lung opacity because these conditions can appear very similar in X-rays. We used a tool called Grad-CAM to clarify how the model makes its decisions. This tool highlights which areas of the X-ray the model focuses on when making a choice. It shows us that the model considers specific parts of the image, rather than just the background.

Using a model that integrates CNN and LSTM is an effective way to automatically analyze X-ray images for lung diseases. The model performs well. We can understand its decision-making process, but it could improve further if we had more images for training.

VI. CONCLUSION

Our hybrid CNN-LSTM model does a great job of sorting chest X-ray images into groups. This is because it does both feature extraction and sequential learning. The model can tell the difference between pictures of normal lungs, viral pneumonia, and lung opacity. It does this with performance and gets it right about 82% of the time.

We also used Grad-CAM visualization to make the system easier to understand. This helps us figure out which parts of the lung are important for the models' predictions. It's like getting a look at how the model chooses what to do. We trust the AI-based diagnosis more because of this.

The model worked well when we trained it and didn't fit too closely. This means that the model can handle data well. We also used Flask to make a web app that can make predictions and give us explanations in real time. This proves that the system can be useful in real life.

Of course, there are ways to make the model even better. We could use datasets and better ways to optimize things. As of now, the model is a good and dependable way to automatically find lung disease. This project demonstrates the utility of hybrid deep learning models in medical image analysis and clinical decision-making. The hybrid CNN-LSTM model is one such example.

CONFLICT OF INTEREST

The authors declared that they have no conflict of interest.

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