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A study on the Deep Learning Models for Lung Disease Detection from Chest X-Ray Images

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Abstract*- Chest X-ray (CXR) imaging is a popular, inexpensive, and non-invasive diagnostic method for examining lung diseases. However, even radiologists often have lower accuracy with CXR data than more expensive methods like CT or MRI, due to lower precision of CXR images. Here, we present a new hybrid deep learning model of image features obtained through a ResNet50 model and clinical data taken through a Random Forest (RF) classifier. The image processing pipeline involved scaling, background/foreground noise removal, feature augmentation, and data cleaning for the clinical data, to present robust input to both deep learning model and RF classifier. The deep learning image features obtained from the ResNet50 model were fused with clinical data obtained from the RF classifier to complete a final classification. Our results compared model levels of accuracy, precision, recall, and F1-score against modern CNN and RNN baselines. Our experiments on a curated and classified CXR data set demonstrated that our ResNet50+RF hybrid model achieved the best performance, with 92% accuracy, 95.9% precision, 96% recall, and a 96% F1-score; the CNN model achieved an accuracy of 91%. RNN performance was lower overall, with an accuracy of 89%. These conclusions suggest the potential of extracting deep features from an image, while also performing ensemble learning on clinical data to improve classification accuracy with a scalable model for real-world clinical decision support systems.

Keywords- ***Deep Learning (DL), Lung Disease Detection, Chest X-Rays (CXRs), Logistic Regression, Decision Trees, Random Forest***

I. INTRODUCTION

Lung disease affects millions of individuals globally and is a serious health issue that places a significant strain on international healthcare systems. An early and precise diagnosis is essential for effective therapy and positive patient outcomes. Lung diseases are still a problem in today's highly technologically equipped society. Because the symptoms are frequently incorrect, the disease must be identified at an advanced degree of severity. Experts advise using the radiographic diagnosis procedure when a patient exhibits symptoms such as coughing, sputum, or blood. Each year, lung infection-induced pneumonia kills thousands of people [1]. Magnetic resonance imaging (MRI), ultrasounds, and CXRs have all recently played a significant role in improving the accuracy of human disease diagnosis. Through more accurate disease diagnosis, significant advancements in medicine and medical research have helped people improve their quality of life. The inability of medical experts to accurately diagnose illnesses in recent years has resulted in overuse of healthcare resources and legal problems for both patients and doctors. Machine learning (ML), deep learning (DL), and statistical analysis are all helpful techniques for computer-aided diagnosis. [2].

Recently, DL and CNNs have become effective tools for medical picture interpretation. Its capacity to discern intricate patterns and interpretations from data has been crucial in radiography [3]. DL can improve prediction accuracy and generalization even with more processing resources and training time, indicating that it has a greater learning capacity. Compared to regular ML, DL might be able to automatically and quickly extract information from an image. The DL methodology can easily handle this, whereas traditional ML systems struggle to distinguish sounds and images with similar properties [4]. The major contributions of the paper includes,

- Suggest a DL model for lung disease prediction with improved performance for lung disease classification
- Evaluate the model's performance in terms of F1-Score, recall, accuracy, and precision

The structure of the paper is as follows: The relevant work for predicting lung diseases using ML and DL techniques is presented in Section 2. Section 3 offers the methods used in this study for prediction followed by efficiency estimation in section 4. The article is concluded in Section 5 with its shortcomings and future directions.

II. RELATED WORKS

Numerous studies have already been conducted by researchers worldwide, with promising results. Early lung cancer diagnosis is made easier by medical practitioners by DL-based lung cancer forecasts. By connecting the field of medicine to automated systems, computer-aided diagnostics is believed to be advantageous. To determine a certain condition, several models are tested using CT scans or CXR pictures as input. Finding the best DL techniques for lung disease prediction is the goal of a study in [5]. Goyal and Singh (2023) presented a framework for pneumonia and Covid-19 detection from chest X-ray images. The proposed approach uses the modification of image quality to identify image ROIs dynamically, extracting a tailor-made invariant and robust features to apply soft computing and RNN-LSTM models for classification purposes During testing upon publicly available datasets, they compared their approach against other approaches and recorded superior accuracy to that of state-of-the-art methods[6].

Shamrat et al.(2023) presented a multiclass lung disease classification model called MobileLungNetV2 that was fine-tuned using the ChestX-ray14 FDA dataset. Improvements in classification accuracy were conducted by reporting the classification accuracy, precision, recall, and specificity as well as the use of Grad-CAM localization and visualization methods. The MobileLungNetV2 has achieved classification accuracy of 96.97% and achieved higher precision, recall and specificity measures than other methods of image transfer learning presented in the published literature base[7].

Priyadarsini et al. (2023) proposed a framework for detecting pneumonia, tuberculosis, and lung cancer from X-ray and CT images. The models used included Sequential, Functional, and Transfer. The Sequential model achieved 98.55% F1 for pneumonia only, whilst Functional achieved 99.9% accuracy for lung cancer, which surpassed previous methods[8]. Zou et al. (2024) proposed an ensemble deep learning model that incorporates chest X-ray images and clinical parameters, to screen and stage COPD. Trained on multicceter data (1055 participants), the model achieved AUC 0.969 (internal) and 0.934 (external) for COPD detection, and up to 0.894 for severity prediction, outperforming the two separate modalities[9]. The table-1 lists the various studies in the literature with regard to lung disease detection using ML and DL algorithms.

Table -1 Recent studies in the literature for Lung Disease prediction using ML and DL

Author Year	Method	Dataset	Score
Ishwerlal et al, 2024[1]	Median Filtering , Local Gabour binary Pattern (LGBP),Ensemble,classifier DNN,LSTM, DQN, DBN	Normal, Pneumonia affected and COVID-19 dataset	Accuracy
Alshmrani et al, 2023[2]	CNN VGG19	Publicly available dataset form RSNA, SIRM and Radiopaedia	Accuracy, Recall, Precision, F1-Score and AUROC
Chandre et al,[3]	CNN	COVID, lung cancer, pneumonia, and tuberculosis-X-ray images	Accuracy
Deepapriya et al., 2023[5]	KNN, RF, SVM, Decision tree with Improvised Grey Wolf(IGWA), Corw Search(ICSA), Cuttle Fish(ICFA)	C19RD and CXIP	precision, recall, accuracy and Jaccard index.
Goyal et al, 2023 [6]	ANN, SVM, KNN, RNN with LSTM	C19RD and CXIP	Precision, Recall, Specificity and F1-Score
Farhan et al, 2023[7]	2D CNN Adaboost, SVM, RF, Back propagation Neural network (BPNN),DNN	C19RD and CXIP	Accuracy Complexity
Jasmine et al, 2023[8]	CNN , Sequential, functional and Transfer	Open source from Kaggle Tuberculosis and Pneumonia	Accuracy, Recall, F1-Score , specificity
Zou et al , 2024'[9]	Efficient Net and RF	clinical dataset	Accuracy and AUC
Podder et al, 2023[10]	ResNet152V2; DenseNet201; XceptionNet	Normal and Pneumonia affected and COVID-19	Accuracy
Thanh et al., 2023[11]	VGG19, Resnet50, Densnet201	ImageNet dataset	Accuracy

III. Methodology

The general framework of the methodology used in this study is shown in figure 1. The method uses both CXR images and clinical information of the lung diseases. The data preprocessing of CXR images includes, resizing, noise removal, feature extraction and augmentation. The clinical information is also preprocessed for missing values, incorrect values and the removal of irrelevant features. The hybrid classifier works as follows

1. The preprocessed CXR images is then fed into ResNet50 to extract the output
2. The clinical information is then classified using RF.
3. Then the both classifier outputs combined to derive the prediction results

The performance of the suggested model is then evaluated using the appropriate classifier.

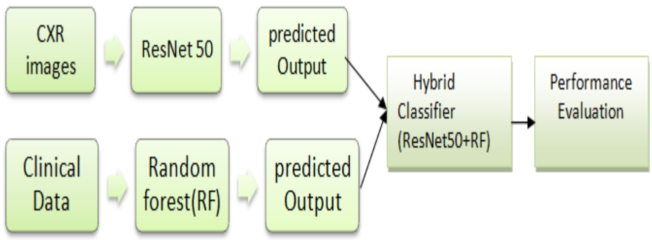

Figure 1 General Framework for the proposed study.

A. ResNet50:

Zero padding is used to preserve the input spatial resolution before the spatial convolution. The above illustrates a layer which is performing convolutional layers which outputs low-level features as edge features. The max pooling tries to retain the maximum amount of information while decreasing the spatial dimension. Then, comes the layer with a ReLU activation function which allows for a non-linear process/ structure relying onto some aspect of spatial structure. The ReLU layer is then followed by a batch normalization layer in order to stabilize the process and/or increase training speed. The last four layers (2-5) continue to add layers sequentially and let guarantees, sequentially, and learn to represent and order representation of features that is even more abstract with a higher level of representation and complexity.

Every stage would probably be a series of convolutional layers, which might or might not have normalization and activation functions. After convolutional layers, the average pooling (AVG Pool) is used in order to reduce the spatial dimension of the feature map without losing spatial invariance. The Flatten layer converts the multi-dimensional feature maps into a vector of 1D. This vector is propagated to fully connected (FC) layers, a classifier, which transforms the features to the output space (e.g., class probabilities). The Output layer then finally makes the prediction.

This hierarchical architecture provides hierarchical feature learning from low-level to high-level representations that can be applied to difficult image classification or recognition problems. [12,13]. Figure 2 displays the layers of the ResNet50 Architecture.

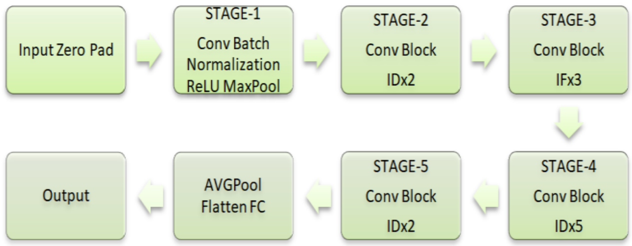

Figure 2 ResNet50 Architecture

B. Random Forest (RF)

RF is an ensemble learning approach that increases the reliability and accuracy of predictions by training many trees and combining their predictions. It trains trees on a random sample of observation and compresses these predictions to a single prediction. The randomness of RF is designed to minimize overfitting, which is a key limitation of a single decision tree. The use of random trees tends to further improve generalization. RF has a two-step training process that will consist of first building a decision tree (DT). Based on its present state, a decision tree builds binary partitions through all possible variable-value pairs to split the data into. These splits recur until it reaches either the maximum depth of the tree, or it can no longer produce meaningful splits of the data.

RF is a powerful, versatile, and efficient machine learning technique that may be applied to a variety of text processing tasks. It is an essential tool for any data researcher using NLP because of its capacity to manage multidimensional data and draw conclusions regarding feature importance [14].

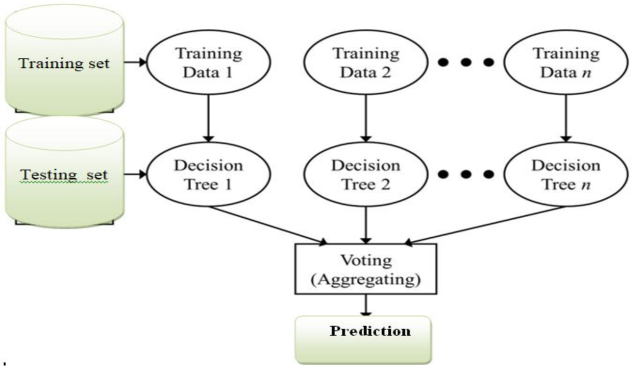

Figure 3 Random Forest Architecture

IV. Findings and Discussion

The suggested method is compared and contrasted with the CNN and RNN, the widely used DL techniques. The experiment is conducted using python in a colab environment.

A. Dataset Description

CXR imaging is a popular, quick, and non-invasive method. The primary scanning technique for chest exams is computed radiography (CXR), which has a less processing time and a radiation exposure. The quality of CXR images is lower than that of images obtained with other modalities, such as CT and MRI. It is more frequent to employ DL to get the same findings as other modalities because CXR is of low quality. As a result, CXR can produce a lot of data for the development of effective DL algorithms [15].

A variety of patients provide the clinical dataset that is employed by the RF classifier. A 70% training dataset was used to train each classification method, which was then used to classify the 30% test dataset.

B. Performance Analysis

The model performance is assessed by evaluating F1-score, recall, accuracy and precision metrics. Accuracy is the number of correct predictions (TP or TN) divided by the number of predictions made. Precision is the percent of true positives with respect to predicted positives. Recall is true positives divided by true positives added to false negatives, which indicates many of the not predicted positives were actually positives. Specificity is the proportion of TN (True negatives) calculated by TN divided by TN added to FN (False negatives).

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

$$F1-Score = 2 * \frac{(Precision*Recall)}{(Precision+Recall)} \quad (4)$$

Table 2- Performance Evaluation

Methods/ Measures	Accuracy	Precision	Recall	F1-Score
ResNet50 +RF	92%	95.9%	96%	96%
CNN	91%	95.45%	95%	95.45%
RNN	89%	93%	92%	93.5%

The table-2 lists the performance metrics calculated using the proposed methods and the contrasted methods CNN and RNN.

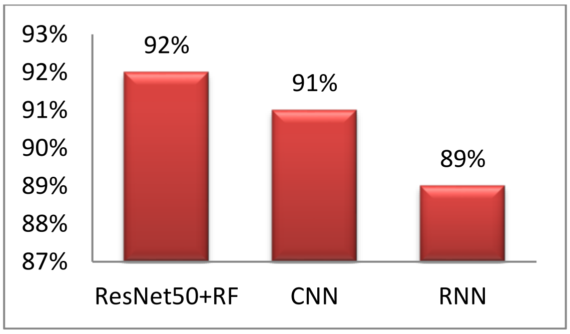

Fig. 4 Accuracy vs DL Methods

Figure 2 compares three different models accuracy performance (ResNet50+Random Forest (RF), Convolutional Neural Network (CNN) and Recurrent Neural

Network (RNN)). ResNet50+RF achieves the best accuracy of 92% performance indicating best performance in the evaluated task, likely a product of the ResNet50 extracting deep features of the image and Random Forest classification capabilities. The CNN closely follows with 91% accuracy performance indicating it was also able to learn features spatially with reasonably good performance with image data. RNN had the lowest accuracy performance at 89% suggesting the RNN model is less effective for the evaluated task, potentially due to the sequential aspect of RNN's, where image data may be less suited, like images at × (spatial dimensional), compared to the more traditional CNN based models. Overall the results show that hybrid models such as ResNet50+RF appears to result in the highest classification accuracy.

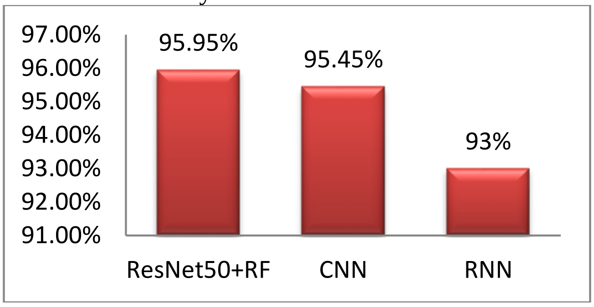

Fig. 5 Precision vs DL Methods

In figure 5, the comparisons on precision of three DL methods are presented. Deep learning method ResNet50 with Random Forest (RF) yields the precision of 95.95% (classifying one stage too early), then CNN with 95.45% (classifying two stages too early) , then RNN with 93%. This indicates that ResNet50+RF has the best precision.

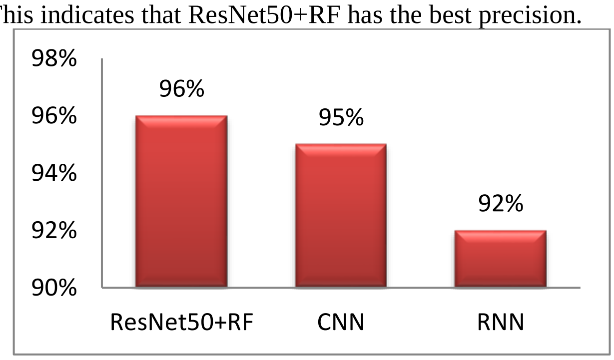

Fig. 6 Recall Vs DL Methods

In figure 6, the recall performance of three deep learning methods is compared. ResNet50+RF achieved 96% recall, followed closely by CNN at 95% and then RNN at 92%. This means that ResNet50+RF is also the most successful at interpreting relevant instances, since it has the best recall of both CNN and RNN after examining the precision of all 3 deep learning methods.

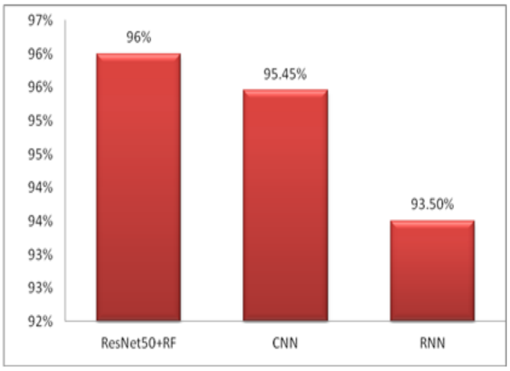

Fig. 7 F1-Score Vs DL Methods

Figure 7 compares all three DL approaches by their accuracy. ResNet50 + RF have the highest value with a score of 96%, with CNN having a score of 95.45% and RNN having a score of 94.50%. This shows that, in general, ResNet50 + RF show better overall performance than the other models.

V. Conclusion

This study has introduced a hybrid framework built upon a deep learning model that combines image features derived from ResNet50 with clinical features classified with Random Forest, to enhance the diagnostic power of lung diseases when analyzing Chest X-ray (CXR) images. The model outperformed standard baselines with traditional CNN and RNN models, achieving 92% accuracy, 95.9% precision, 96% recall and a 96% F1-score on a curated dataset using the CXR model. The results suggest that multi-modal data integration improves classification. However, there are still deficiencies within this study. The sample size was limited and possibly did not capture all the heterogeneity of the patient populations, imaging scenarios and even disease variations when diagnosing lung disease in practice. In addition, the clinical features were limited to the features available in the records. Lastly, the interpretability of the model would impose challenges regarding the clinical use of the model, given that the explainability of AI in practice is vital. Moving forward, the next steps are to validate the framework on larger multi-centre datasets, including other clinical features and genomic features, and exploring explainable AI. In addition, real-time deployment of the framework as well as comparison with emerging architectures, such as transformers or multi-task learning models, to maximise scalability and clinical usage.

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