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Utilizing Hybrid CNN Model and Machine Learning Techniques for the Identification of Pulmonary Fibrosis

1st Anant Saraswat
Department of Computer Science and Engineering
Sanskrithi School of Engineering
Puttaparthi, Andra pradesh, India
Anant.saraswat@live.com

2nd Upasana
Department of Computer Science and Engineering
National Institute of Technology Patna
Patna, India
upasanac.phd19.cs@nitp.ac.in

3rd Bhaskar Naik K
Department of Computer Science and Engineering
Sanskrithi School of Engineering
Puttaparthi, Andra pradesh, India
Bhaskar403@sseptp.org

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***Abstract*—Pulmonary fibrosis is a progressive lung disorder characterized by scar tissue formation, leading to a deterioration of the patient's respiratory function. The identification of such diseases heavily relies on medical imaging techniques, such as high-resolution computed tomography (HRCT) and radiographic images (X-rays). Unfortunately, the high cost and potential risks associated with radiation exposure make HRCT inaccessible to the majority of people. This paper proposes a hybrid model for classifying fibrotic and healthy lungs from chest X-ray images. Convolutional Neural Networks (CNNs) have emerged as the most widely used deep learning models for medical image classification. However, different CNN architectures employ distinct approaches to learning and interpreting images. So, the features of three well-known CNNs: Xception, InceptionResnetV2, and DenseNet121, are fused to form a comprehensive feature representation. Principal Component Analysis (PCA) is applied to alleviate overfitting and reduce dimensionality. Subsequently, a random forest classifier is employed on the principal components for accurate classification. By integrating these methods, we aim to enhance the classification of pulmonary fibrosis and promote early detection for improved patient outcomes.**

***Index Terms*—Pulmonary Fibrosis, Machine Learning, CNN**

I. Introduction

Pulmonary fibrosis is a chronic disorder that scars the lung tissues and worsens the patient's condition. This scar tissue thickens and stiffens the lungs, making it difficult for them to function properly. Symptoms include shortness of breath, a dry cough, feeling tired, weight loss, and nail clubbing [1]. Over time, the condition worsens, leading to shortness of breath, coughing, fatigue, and a reduced ability to engage in physical activities. Multiple terms have been applied to patients with pulmonary fibrosis, including diffuse parenchymal lung disease, usual intestinal pneumonia (UIP), and nonspecific interstitial pneumonia (NSIP) [2], [3].

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HRCT plays a crucial role in diagnosing pulmonary fibrosis due to its ability to provide high-resolution images of the lungs. However, the drawbacks of HRCT, like high radiation exposure and cost, make the scanning process challenging. In contrast, X-rays are more readily available and cost-effective routine diagnostic procedures. However, the drawbacks of X-rays are their limited detail and resolution, making it challenging to visualize delicate anatomical structures and detect subtle abnormalities. Using deep learning algorithms, it is possible to train models on large datasets of high-quality X-ray images that help to overcome this limitation by leveraging their ability to extract intricate details from images. By utilizing the power of deep learning, radiologists can benefit from computer-aided detection and diagnosis tools that assist in identifying subtle abnormalities that may be challenging to detect with the naked eye.

Machine learning and deep learning algorithms have revolutionized medical image classification by providing accurate and efficient automated analysis in a limited time. Several other works have been done for the classification of diseases like COVID-19 [6], tuberculosis [7], breast cancer [8], pneumothorax [5], tumours [9] using the HRTCs, X-rays and MRIs. Upasana et al. [5] proposed an approach for pneumothorax classification using a modified xception model [10]. The attention mechanism is applied to the xception model to draw special attention to the relevant features. Arpaci et al. [11] proposed an approach for predicting the COVID-19 disease using 14 clinical features. The authors evaluated six different classifiers Classification via Regression (CR) classifiers produce the best result.

In this work the strength of three best performing CNNs combined together to get more accurate classification between pulmonary fibrosis and healthy images. As various Convolutional Neural Networks employ diverse approaches to learn and interpret images.

The contribution of this work is listed below:

- The performance of seven deep learning models, namely, VGG16, Xception, ResNet50, ResNet101V2, Inception-ResNetV2, DenseNet121 and DenseNet169, are evaluated to get the best-performing models.
- Features from three best-performing models are fused to form a comprehensive feature set.
- The dimension of the features set is reduced by applying principle component analysis.
- Four classifiers, namely, support vector machine (SVM), decision tree, random forest classifier and multi layer perceptron (MLP), are applied to the refined features for classifying pulmonary fibrosis and healthy X-ray images.

In the next section, we discussed the works related to the proposed approach. Section three discusses the dataset and preprocessing performed on it. Section four discusses the proposed method, and section five includes the conclusion and future work.

II. Related Work

For the last few years, deep learning models have been used vastly in medical imaging for fast and accurate classification of diseases.

Lie et al. [15] proposed a model to classify and segment the fibrotic lungs from chest X-ray images. The authors used the Inception ResNetV2 model for classification and achieved an accuracy of 93%. In addition, they utilized an attention-Unet model for the segmentation of lungs. Syed et all. [13] presented a deep learning model that utilizes transfer learning for the classification of pulmonary fibrosis based on chest CT images. They employed the ResNet50 model, employing an optimized learning rate of 0.000625, and attained an impressive accuracy of 99.22%.

Shamrat et al. [16] introduced a model called LungNet22, which utilized the VGG16 architecture with additional layers and fine-tuned hyperparameters. Their model was designed to classify ten diseases, including pulmonary fibrosis, and demonstrated notable performance.

Bharati et al. [17] proposed an approach that combines the strengths of different deep learning models and methods to improve the accuracy and reliability of disease detection. By leveraging the capabilities of various architectures, such as convolutional neural networks, recurrent neural networks (RNNs), and transfer learning, hybrid deep learning models can effectively analyze X-ray images and identify patterns associated with different lung diseases. Integrating multiple models and techniques enables a more comprehensive and robust analysis, leading to enhanced diagnostic accuracy in detecting lung diseases from X-ray images.

Among the aforementioned studies, only a limited number of papers specifically concentrated on the identification and classification of pulmonary fibrosis. Additionally, no research was found regarding the extraction of more informative features from X-ray images. With can integrate this technique into text classification also. [19]

III. Dataset

The National Institutes of Health (NIH) released a dataset in 2017 that comprises 14 X-ray images featuring different lung diseases [12]. A total of 1454 images are considered for the evaluation. The train and validation are divided in the ratio 80% and 20%. Further, the train data is divided in the ratio 80% and 20% for training and testing purposes. The details of data fraction is provided in table I.

TABLE I
Data Distribution

Class	Train	Validation	Test	Total
Pulmonary Fibrosis	466	116	145	727
No Findings (Healthy)	466	116	145	727
Total	**932**	**232**	**290**	**1454**

IV. Methodology

The proposed hybrid model combines the features of the three highest-performing CNN models, Xception, Inception-ResNet50, and DenseNet121, to improve classification performance. The resultant feature representation is more informative due to the incorporation of model-specific information. In tandem with the expansion of the feature set, the dimensional of the feature set grows, which may result in overfitting. To solve this issue, principal component analysis is employed. Furthermore, four classifiers, SVM, DT, MLP and RFC, are used for the classification. Figure 1 shows the architecture of the proposed approach. As shown, the X-ray images are passed concurrently through three CNN models.

All three models, DenseNet121, Xception, and IncepionResNetV2, take the input size of 224×224 and produces features of size 1024, 2048, and 1536 respectively. After feature concatenation, the combined features set is of size 4608, out of which 25% features a retained for the classification using the principal component analysis.

Total of 1152 principal components are used by the random forest classifier for the classification. The hyper-permeates of random forest classifier is given in Table II.

TABLE II
Hyper-parameters used in the random forest classifier.

Hyper-parameters	Values
N_estimators	120
Max_depth	5
Min_samples split	2

A. Principal Component Analysis

Principal Component Analysis, the reduced features are typically referred to as the principal components or the transformed features. PCA capture the most significant data and discard the less informative once. The transformed features obtained through PCA are usually ordered by their importance, with the first component explaining the most variance in the data, followed by the second component, and so on [18].

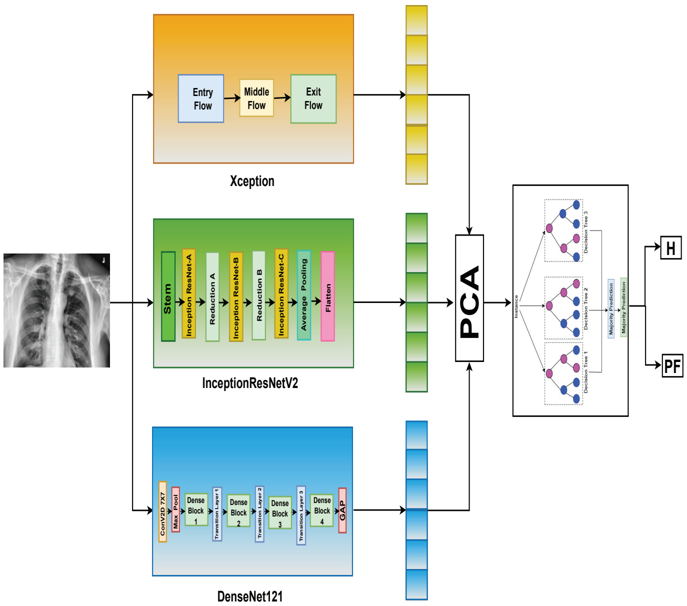

Fig. 1. Architecture of the Proposed Approach.

TABLE III
PERFORMANCE OF DIFFERENT PRE-TRAINED MODELS

Model Name	Accuracy	Pathology	Precision	Recall	F1-Score	AUC
VGG16	46%	Fibrosis	46%	100%	63%	0.50
		Healthy	0.0%	0.0%	0.0%	0.50
Xception	66%	Fibrosis	73%	42%	53%	0.77
		Healthy	64%	87%	74%	0.77
ResNet50	54%	Fibrosis	33%	1%	1%	0.54
		Healthy	54%	99%	70%	0.54
Inception ResNetV2	66%	Fibrosis	54%	83%	69%	0.77
		Healthy	79%	51%	62%	0.77
DenseNet121	66%	Fibrosis	72%	44%	54%	0.73
		Healthy	64%	85%	73%	0.73
DenseNet169	51%	Fibrosis	47%	62%	53%	0.55
		Healthy	56%	42%	48%	0.55

V. Result and Discussion

In the first stage of the model, six widely used CNN models, including VGG16, ResNet50, Xception, ResNetInceptionV3, DenseNet121, and DenseNet169, are tested to determine the best-performing models. The models with the best performance are the Xception, the ResNetInceptionV3, and the DenseNet121. And the model with the worst performance is VGG16, with precision and recall scores of 0% each. The ResNet50 model has 1% precision and recall, making it the second-worst-performing model. DenseNet121 shows a good performance. However, when the extended version of densenet121, which is called densenet169, is utilised, the performance drops significantly.

Table III Shows the performance of all CNN models. As shown, the test accuracy of Xception, InceptionResNetV2 and DenseNet121 is 66% each. Xception gives the best performance with 69% precision, 65% recall and 64% F1-score, ResNetInceptionV2 gives the second best performance with 67% precision, 67% recall and 66% F1-score, DenseNet121 gives the third best performance with 68% precision, 65% recall and 64% F1-score.

Five classification algorithms, namely Support Vector Machine, Decision Tree, Multi-layer Perceptron, and Random Forest Classifier are applied to the principal components. The performance of each classifier is presented in Table IV. The SVM classifier exhibits poor performance, achieving an accuracy of 53.09%, precision of 54%, recall of 54%, and an F1-score of 52%. The MLP classifier performs better with an accuracy of 75.94%, precision of 77%, recall of 75%, and an F1-score of 76%. The DT classifier is the second-best performing model, achieving an accuracy of 92%, precision of 92%, recall of 92%, and an F1-score of 92%. The RFC classifier demonstrates the highest performance, achieving an accuracy of 93.09%, precision of 93%, recall of 90%, and an F1-score of 92%. Figure 2 shows the metrics for each class and Figure 3 shows the confusion matrix of the proposed approach. The AUC (area under the Receiver Operating Characteristic (ROC) curve) is shown in Figure 4.

TABLE IV
PERFORMANCE OF DIFFERENT CLASSIFIERS

Classifier	Accuracy	Pathology	Precision	Recall	F1-Score	AUC
SVM	53.09%	Fibrosis	56%	38%	45%	68
		Healthy	52%	69%	59%	69
MLP	75.94%	Fibrosis	76%	76%	76%	70
		Healthy	78%	74%	76%	73
DT	92%	Fibrosis	92%	92%	92%	94
		Healthy	92%	92%	92%	92
RFC	**94.03%**	Fibrosis	90%	95%	92%	94
		Healthy	95%	89%	92%	94

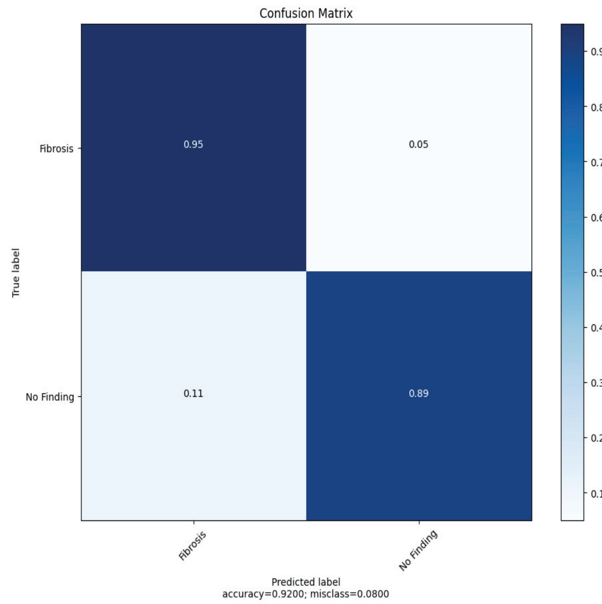

Fig. 3. Confusion matrix of the proposed approach.

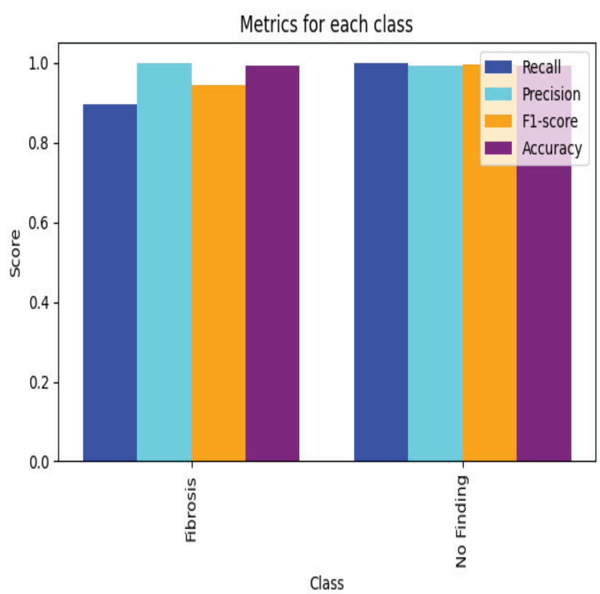

Fig. 2. Performance metrics of the proposed approach.

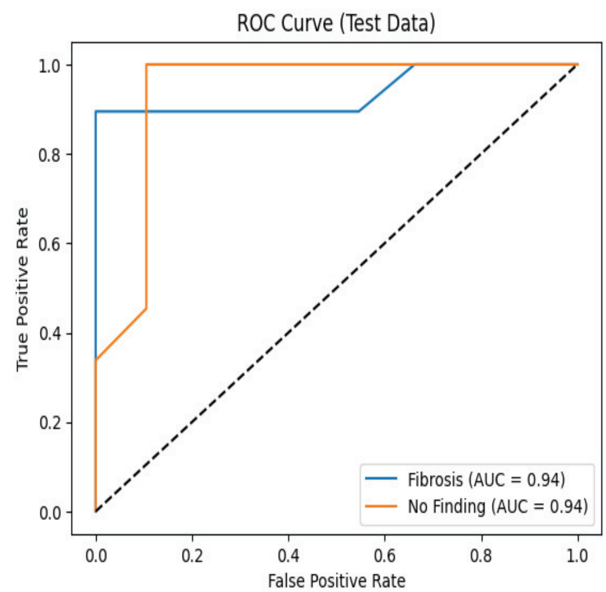

Fig. 4. Area under the Receiver Operating Characteristic (ROC) curve.

VI. Conclusion and Future Work

Pulmonary fibrosis identification is essential for early intervention, accurate diagnosis, treatment planning, prognosis assessment, patient support, and research advancements. Timely and accurate identification of pulmonary fibrosis can lead to improved patient outcomes, better management strategies, and the development of innovative therapies for this challenging condition. In this study, we presented a novel approach for classifying pulmonary fibrosis based on chest X-ray images. To enhance the feature representation, we combined the features extracted from the top-performing convolutional neural networks. Furthermore, we employed principal component analysis to mitigate the issue of overfitting by reducing the dimensionality of the resulting feature set. The random forest classifier was employed to classify the principal components obtained from the application of principal component analysis. From the proposed approach, we can conclude that the application of combined deep learning and machine learning techniques can boost the classification performance.

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