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A System to Classify Chronic Obstructive Pulmonary Disease using Pre-trained-Densenet201 with TSA

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ABSTRACT

COPD (Chronic obstructive pulmonary disease), ranking as the 3rd most common cause of death worldwide, frequently goes undiagnosed. Yet, the detection of COPD in its early stages is challenging due to the limited presence or mild nature of initial symptoms. In this work, the DL (deep learning) model DenseNet201 is utilized for classifying COPD using the PFT (Pulmonary Function Test) images. Initially, the pre-processing is carried out using the MF (median filter). After the noise elimination process, automated feature extraction and classification is carried out using the Pre-trained-DenseNet201 with TSA (tunicate search algorithm). The presented model provided satisfactory outcomes, attaining the accuracy of 0.985 and an AUC value of 98.73. These results surpass those reported in prior studies utilizing the similar database. Furthermore, the presented approach exhibits superior performance compared to various contemporary methods trained concurrently. This study represents the inaugural application of the Pre-trained-DenseNet201-with TSA model to this specific dataset for the purpose of COPD identification.

1. Introduction

COPD (Chronic obstructive pulmonary disease) is a lung ailment defined by a substantial world prevalence, elevated mortality rates, and considerable medical expenses. Based on the analysis of WHO (World Health Organization), by the year 2030, it is anticipated that COPD will rank as the 3rd leading cause of death worldwide [1]. However, individuals with early-stage COPD may be overlooked, given that they exhibit either no symptom. Frequently, people are diagnosed when they have already progressed to the moderate to severe phase, significantly impacting their lives and leading to a substantial rise in treatment costs [2]. Recognizing the importance of quick identification, it is crucial to identify COPD in its initial stages, as this is accompanied with a less risk of less exacerbations, a decrease in the prevalence of multiple disorder, and less overall expenses. There is an increasing awareness of the necessity to detect COPD at an initial phase [3].

Spirometry serves as the fundamental tool for diagnosing COPD. Despite its significance, there is a notable tendency for under diagnosis, particularly in the early stages of COPD due to its limited sensitivity [4]. To overcome this limitation, CT (computed tomography) has emerged as a valuable alternative. CT scans are employed for capturing and analyzing the occurrence, and patterns of phenotypic abnormality accompanied with COPD. As a widely adopted imaging modality, CT has proven effective in classifying the diverse manifestations of COPD heterogeneities [5]. The extensive use of CT presents an opportunity to leverage these scans for the identification of individuals with COPD, and subsequent confirmation through spirometry can enhance diagnostic accuracy [6].

Previously, the classification of COPD using CT imaging relied on conventional ML (machine learning methods. but, these conventional methods often struggled to capture intricate features. On the other hand, contemporary DL (deep learning) method, whether implemented from the ground up or through fine-tuning, typically demands substantial labelled training data and significant computation and memory sources

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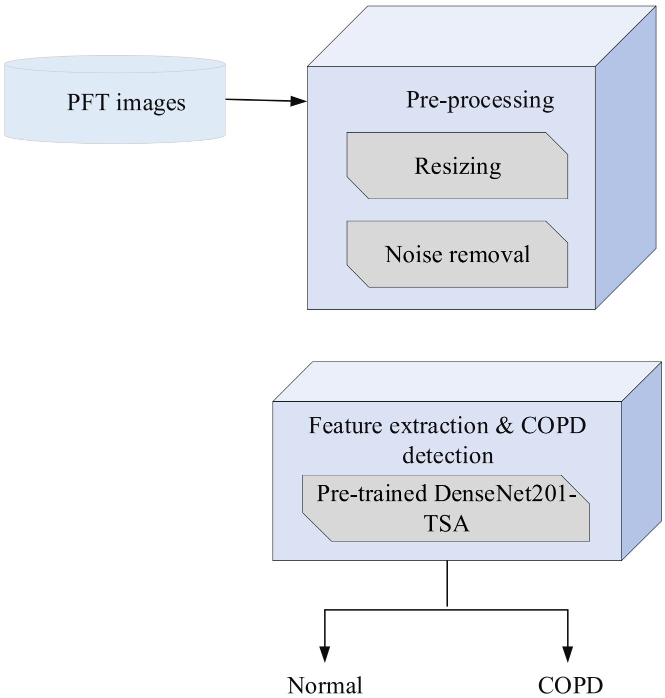


Fig. 1. Workflow of the proposed COPD model.

[7]. Furthermore, due to limitations imposed due to the potential of available graphical processing units, the complete scan images from patients were not fully utilized in the DL models [8]. This work presents a DL model for categorizing the normal and COPD images. The suggested COPD model was not only identified by normal and diseased images but also attained better accuracy.

- To present different models for the diagnosis of COPD.
- To introduce Pre-trained-DenseNet201 for automatic feature extraction and COPD classification.
- To introduce TSA for updation of the weight of Pre-trained-DenseNet201's hyper-parameters.

The following sections are: In Section 2, a succinct overview of prior research efforts concentrating on the identification of COPD is presented. Section 3 outlines the materials employed and expounds upon the proposed COPD. The experimental results are showcased and analyzed in Section 4. Finally, Section 5 concludes the study.

2. Related works

Altan et al. [9] presented the examination of lung sounds based multi-channel by employing statistical features derived from frequency modulation. These modulations were extracted through the application of the Hilbert Huang transformation. Here, the sensitivity and accuracy values achieved 96.3% and 91% respectively.

Schroeder et al. [10] developed COPD model using the pre-trained CNN model using the PET images. Initially, the input images were resized and the COPD images were trained. At last, the AUC value achieved was 0.814.

Li et al. [11] demonstrated GCN (graph convolution network) to identify the COPD. The demonstration was carried out on the Danish lung cancer dataset and achieved better accuracy of 0.77.

Hasenstab et al. [12] suggested a retrospective investigation, based on registration and segmentation of the lung for the automated emphysema quantification. Subsequently, the model underwent testing in a distinct cohort comprising 8951 individuals. By measuring bi-variable thresholds, air trapping and emphysema were established to delineate severity stages on CT scans. These defined stages were then assessed for their predictive capability in terms of progression of disease and death rate, utilizing ML classifiers.

Dhar, Joy et al. [13] introduced *M*-SEN (multi-stage ensemble network) with the GA (genetic algorithm) for COPD detection. Here, the KCM (k-means clustering) was utilized for filling the missing values and the isolation forest was used for removing outliers. Accuracy and the precision values achieved were 0.982 and 0.98 respectively.

Ho et al. [14] introduced a 3D-CNN to classify COPD images using the CT images. 596 CT images were collected from the individuals; finally, accuracy and sensitivity values achieved were 89.3% and 88.3% respectively.

Lopez et al. [15] presented DL model to predict readmission of hospitals for COPD and asthma. Here, the dataset was collected from Yale New Haven Hospital and achieved an AUC value of 0.86.

Table 1
Measures utilized to compute the performance.

Measures	Formulas
Accuracy	$\frac{t_{po}+t_{ne}}{t_{po}+t_{ne}+f_{po}+f_{ne}}$
precision	$\frac{t_{po}}{t_{po}+f_{po}}$
Recall	$\frac{t_{po}}{t_{po}+f_{ne}}$
Specificity	$\frac{t_{ne}}{t_{ne}+f_{po}}$

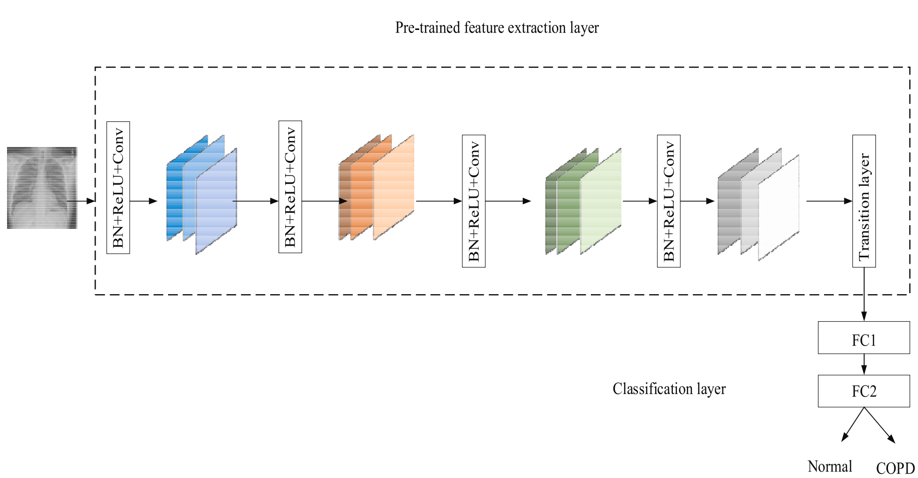
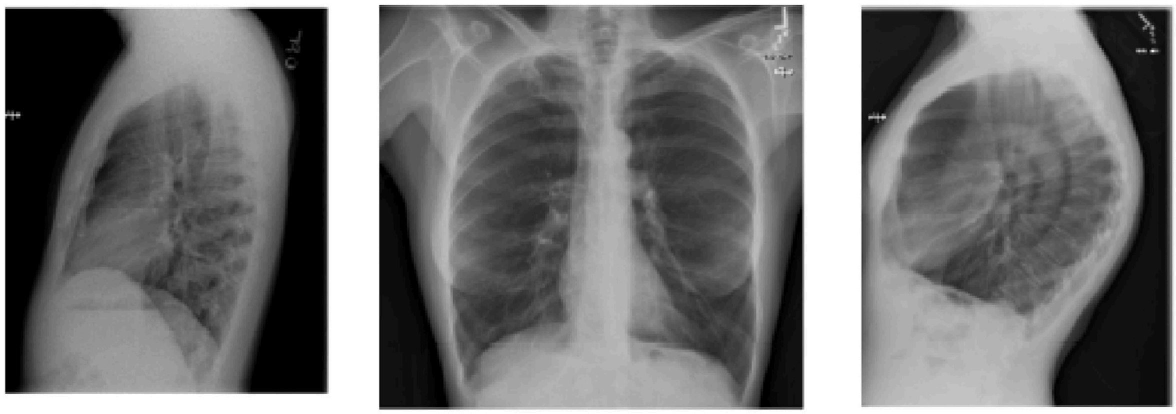


Fig. 2. Structure of pre-trained-DenseNet201.



(a) (b)

Fig. 3. Samples images of the dataset.

Table 2
Comparative analysis.

Methods	Accuracy	precision	Recall	Specificity
CNN	0.892	0.824	0.789	0.883
2D-CNN	0.903	0.831	0.834	0.902
AlexNet	0.912	0.874	0.845	0.924
ResNet	0.914	0.893	0.873	0.931
Denset201	0.956	0.931	0.941	0.942
Pre-trained-DenseNet201	0.966	0.941	0.947	0.948
Proposed	0.985	0.962	0.957	0.967

3. Proposed methodology

COPD is a respiratory condition characterized by abnormalities in the morphological structure of the lungs, varying in severity. Evaluation of COPD typically involves PFT (Pulmonary Function Test) and approaches utilizing CT. Fig. 1 defines the workflow of the proposed COPD model. Here, the pre-processing process is carried out by the MF. Then, the automated extraction of features and classification is carried out by the pre-trained–DenseNet201-TSA.

3.1. Pre-processing

Initially, the input images are resized and the noise removal process is performed by the MF approach. The MF operates by replacing a pixel's value with the middle value of the pixels within a small, adjacent window. The representation of the MF for $m \times m$ pixel windowing is expressed as follows:

$$MF(j(a,b)) = Median(j(a+r, b+t)) \tag{1}$$

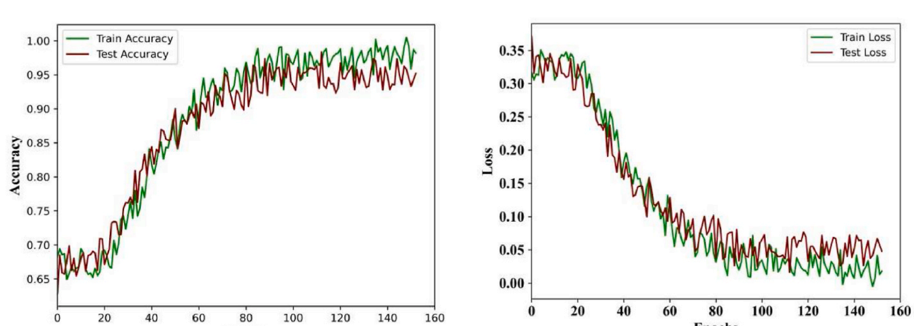
where $j(a,b)$ is the value of pixel.

3.2. Extracting and classifying COPD

After the noise removal process, the DL model pre-trained–DenseNet201 is utilized for automatic extraction of features and classification of COPD. Fig. 2 presents the structure of pre-trained-DenseNet201 and it has 201 layers. This DL model enhances performance by utilizing the prior layers effectively. In this architecture, every layer receives input from the overall set of prior layers and conveys the obtained features forward to the following layers. This design contributes to improved overall robustness. A fundamental characteristic of DenseNet201 lies in its ability to concatenate all the feature maps from prior layers. This facilitates the seamless emergence of feature maps via the following layers, integrating them with new feature maps. The final network iteration presents multiple benefits, including the reuse of features and addressing limitations like explosion and gradient vanish. These Networks are organized into Dense-Blocks, maintaining constant feature map equal in a layer. However, as one progresses over blocks, there is a variation in the filters. There are transition layers in the block and it is essential for down sampling through 1×1 convolution, BN (batch normalization) and 2×2 pooling layer.

3.2.1. Weight updation using the TSA

The TSA represents a population based optimizer designed for tackling global optimized challenges. Every tunicate, with a length of



(a) (b)

Fig. 4. Accuracy loss curve of the suggested pre-trained-DenseNet201-TSA.

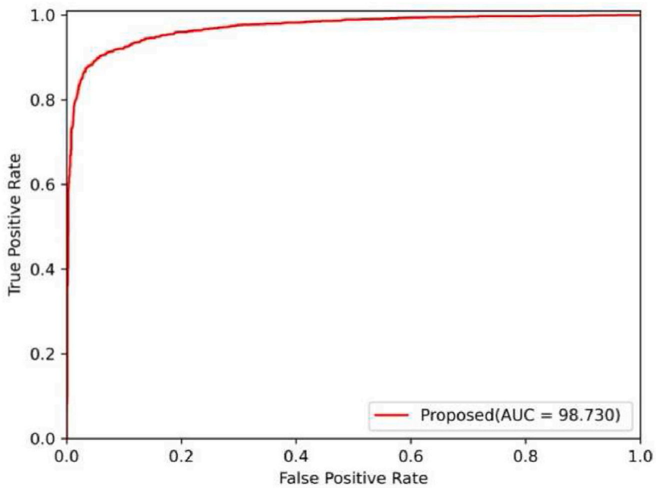


Fig. 5. Confusion matrix of the suggested pre-trained-DenseNet201-TSA.

Table 3
Comparison with recent works.

Methods	Accuracy	precision	Recall	Specificity	AUC
Altan et al. [9]	93.6	–	91	96.3	
Schroeder et al. [10]	0.74	–	0.63	0.832	0.837
Li et al. [11]	77	–	–	–	0.81
Dhar, Joy et al. [13]	0.982	0.98	0.96	–	–
Ho et al. [14]	89.3	–	88.3	–	–
Lopez et al. [15]	–	–	–	–	0.86
Proposed	**0.985**	**0.962**	**0.957**	**0.967**	**98.73**

some millimetres, possesses collective tunicates, connecting all tunicates together. This interconnected feature enables the exchange of information among them. Additionally, every tunicate independently draws in water from the surrounding area and generates JP (jet propulsion). By utilizing this JP mechanism, tunicates alter their direction, creating a fluid-jet like movement. Tunicates exhibit three distinct characteristics during the JP phase. Firstly, to avoid fighting among the tunicate's population during the exploration, every tunicate consistently endeavors to move towards the individual with the highest fitness value and endeavors to maintain proximity to the fit individual. The calculation of this $\overrightarrow{X}$ vector is carried out according to the equations provided below.

$$\overrightarrow{X} = \frac{\overrightarrow{Y}}{\overrightarrow{Z}} \tag{2}$$

$$\overrightarrow{Y} = a_2 + a_3 - \overrightarrow{U} \tag{3}$$

$$\overrightarrow{U} = 2a_1 \tag{4}$$

where $\overrightarrow{Y}$, $\overrightarrow{Z}$ and $\overrightarrow{U}$ are the force of gravity, social interaction and water depth. $a_1, a_2,$ and a_3 are the random values. The value of $\overrightarrow{Z}$ is given as:

$$\overrightarrow{Z} = [W_{\min} + a_1 W_{\max} - W_{\min}] \tag{5}$$

where $W_{\max}$ and $W_{\min}$ are the maximum and minimum values. The motion of the current tunicate to the better one is computed as:

$$\overrightarrow{D} = \left[\overrightarrow{US} - rand \times \overrightarrow{P(z)}\right] \tag{6}$$

where $\overrightarrow{D}$ is the distance among food and tunicate, $\overrightarrow{US}$ is the best tunicate, $\overrightarrow{P(z)}$ is the position of tunicate and *rand* is the random value. The new position of $\overrightarrow{P(z')}$ is given as:

$$\overrightarrow{P(z')} = \begin{cases} \overrightarrow{US} + \overrightarrow{X}D \nearrow when\ rand \geq 0.5 \\ \overrightarrow{US} - \overrightarrow{X}D \nearrow when\ rand < 0.5 \end{cases} \tag{7}$$

The modelling of swarm characteristics for tunicate is mathematically expressed as:

$$\overrightarrow{P(z+1)} = \frac{\overrightarrow{P}(z) + \overrightarrow{P(z+1)}}{2 + a_1} \tag{8}$$

Following stages shows the processes of weight updation of the pre-trained-DenseNet201 by the TSA.

Stage 1: Compute the tunicate's initial population.
Stage 2: Estimate the TSA controls and ending term.
Stage 3: Compute the initial population's fitness.
Stage 4: Choose the tunicate's position by the best value of fitness.
Stage 5: Estimate the tunicate's direction by Eq. (8).
Stage 6: The tunicate's position is updated which are not on the searching area.
Stage 7: Estimate the value of fitness of tunicate's position.
Stage 8: The process is repeated until the ending criteria are met.
Stage 9: Once the ending criteria are met, record the better tunicate's position.

4. Results analysis

Evaluation of the suggested COPD is carried out on the Python tool. The hyper-parameters like epochs (160), size of batch (128), learning rate (0.001), iterations (100) and population size (50) are considered. Table 1 defines the measures utilized to compute the performance and is based on the variables like true positive t_{po}, true negative t_{ne}, false positive f_{po} and false negative f_{ne}.

4.1. Dataset

Prior to the application of pre-processing, for the validation and test sets 10% and 20% of the images are designated, considering a total of 4433 individuals. Following the pre-processing process, the allocation adjusts to 10% and 18% to validate and test. The study involves a comprehensive dataset of 6751 PFT data. In this PFT data, there are 4774 images (training), 755 (validation), and 1222 (testing). Fig. 3 defines the samples images of the dataset.

4.2. Comparative analysis

Table 2 depicts the comparative analysis of the various approaches like CNN, 2D-CNN, AlexNet, ResNet, Denset201 and pre-trained-DenseNet201 are compared with the proposed COPD (pre-trained-DenseNet201-TSA) model. It is observed that the proposed COPD attained better accuracy of 0.985, precision of 0.962, recall of 0.957 and specificity of 0.967 respectively.

Fig. 4 states the accuracy loss curve of the suggested pre-trained-DenseNet201-TSA by varying the epochs from 1 to 160. The analysis is taken for train and test performances. It is proved that the suggested pre-trained-DenseNet201-TSA attained better accuracies and losses after the 100th epochs.

In Fig. 5, the curves depicting the AUC (Area Under the Curve) and ROC (Receiver Operating Characteristic) measures for the pre-trained-DenseNet201-TSA on the utilized dataset are presented. The visual representation illustrates robust classification performance with a less false positivity rate. The red line corresponds to the detection rate, demonstrating a maximum level of effectiveness. This implies that the outcomes of the pre-trained-DenseNet201-TSA attained significant AUC value of 98.73%. Table 3 presents the comparative analysis of the recent works. It is analyzed that the proposed pre-trained-DenseNet201-TSA outperformed all conventional models.

5. Conclusion

This research presents an innovative pre-trained-DenseNet201-TSA model that employs an optimizer for early COPD identification. The purpose of this work was to assist medical experts in delivering timely and appropriate treatment, ultimately contributing to the preservation of patient's lives. The analysis was carried out on the PFT data and it was noted that the proposed COPD model outperformed all conventional approaches. In the future, different DL models with different adaptive optimizers will be utilized for determining the severity of COPD.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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