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Research Article

Chronic Lower Respiratory Diseases detection based on Deep Recursive Convolutional Neural Network

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Abstract:

Recently, symptoms of Chronic Obstructive Pulmonary Disease (COPD) have been identified concerning long-term continuous treatment. Furthermore, predicting the life probability of patients with COPD is crucial for formative ensuing treatment and conduct plans. Additionally, it plays a vital role in providing complementary solutions using technologies such as Deep Learning (DL) to address experiments in the medical field. Early and timely analysis of clinical images can improve prognostic accuracy. These include COPD, pneumonia, asthma, tuberculosis and fibrosis. Conventional methods of diagnosing COPD often rely on physical exams and tests such as spirometers, chest and genetic analysis. However, respiratory diseases pose an enormous comprehensive health burden for many patients. Thus these methods are not always accurate or obtainable. However, succeeding in their accuracy involves a nonspecific diagnosis rate, time-consuming manual procedures, and extensive clinical imaging knowledge of the radiologist. To solve this problem, we use a Deep Recursive Convolutional Neural Network (DRCNN) method to detect chronic lower respiratory disease. Initially, we collected the images from the Kaggle repository, and evaluate the result based on the following stage. The first stage is pre-processing using a Gaussian filter to reduce noise and detect the edges. The second stage is segmentation used on Image Threshold Based Segmentation (ITBS), used for counting the binary image and separating the regions. In the third stage, we use the chi-square test to select the best features and evaluate the image values for each feature and threshold. Finally, classification using DRCNN detects CLRD classifying better than the previous method. In synthesis, CLRD can be detected by many staging measures, such as sensitivity, specificity, accuracy, precision, and Recall

1. Introduction

The health sector is uniquely associated with other sectors and utilities as one of the most critical segments. In addition, these sectors also serve as essential industries where people assume the highest quality of diagnosis, treatment and amenities for the money they devote. The

consequence of disease on health is increasing rapidly due to environmental change, climate change, and lifestyle.

COPD causes persistent respiratory symptoms and ventilator failure. Among these, the main pathological feature is bronchial airflow limitation. The overall health of the lungs and peripheral respiratory classification can be observed. It is reflected in a safe, non-invasive and cost-effective medical technique. Chronic bronchitis is a disease of inflammation caused by excessive coughing and mucus production in the routes. Coronary artery disease, weight loss, obesity, cognitive impairment, anorexia, and lung cancer are predisposing factors for COPD.

The risk of lung disease is substantial, mainly in developing and low- and middle-income countries, where millions of people are exposed to paucity and air pollution. The World Health Organization estimates that more than 4 million people die each year from diseases correlated to indoor air pollution, such as asthma and pneumonia.

However, the images and sounds from various medical devices can be limited due to their subjectivity, clarity and complexity. Unfortunately, the disease is often detected late; thus, patients miss out on the struggles they require. Poorly accomplished staff and those with inadequate testing are prone to poor-quality of spirometry.

The contribution of this study is that we have collected the necessary images from a Kaggle repository to overcome this problem, and these techniques can be evaluated based on the following levels. Then, we first perform pre-processing using a Gaussian filter to reduce noise and detect edges from the images. Next, the ITBS method handles image segmentation as a second step to enable image binary image counting and segmentation. Then, the best features can be selected using the chi-square test to estimate the image values for each feature and threshold. As a last step, chronic lower respiratory diseases can be diagnosed and classified by the newly proposed DRCNN method to perform better than the previous method. In this section, the basic framework for CLRD respiratory disease introduced in Figure 1 is well presented. The first step is to evaluate the processing of images using a Kaggle repository to collect data. Then, it provides models such as pre-processing, image segmentation, feature selection, and image classification to get the evaluation of the images.

2. Literature Survey

There are a number of works done on this subject and summarized in here [1-20]. K. P. Exarchos et

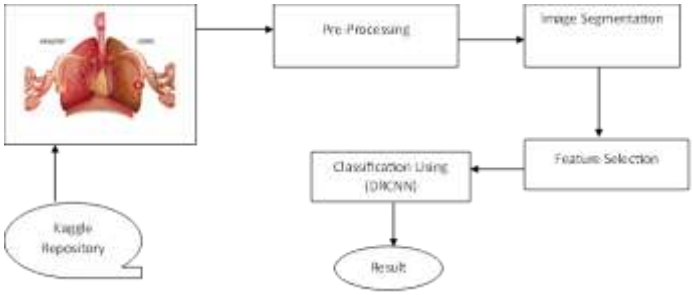

Figure 1. *The Basic Configuration of Disease Diagram*

al, [11] noted that COPD techniques could be used to statement various chronic diseases with diverse symptoms and complex interactions to accomplish a restored objective for Artificial Intelligence (AI).

Novel distributed information of worsening symptom systems with substantial adverse patient outcomes is Acute Exacerbations of COPD (AECOPD). The elevated, highly heterogeneous phenomena are associated with increased airway and systemic swelling and functional changes [17].

A. Roy et al, [3] proposed a DL framework for 2-class and 5-class COPD sorting using Deep Belief Network (DPN) and Extreme Learning Machine (ELM) classifiers, individually. A Mel-spectrogram slice illustration learning framework can be employed to classify 2-class and 5-class COPD.

K. L. Khatri et al, [10] mentioned that an Artificial Neural Network (ANN) method could generate the essential classifier based on them. Multi-layer perceptrons and backpropagation algorithms can be used to forecast peak procedures in respiratory disease patients.

S. B. Shuvo et al, [18] proposed that complex-level feature maps of lung sounds can be implemented to classify respiratory diseases from individual respiratory cycles using a lightweight convolutional neural network (CNN) framework. Accumulated, surrounds based on the presented scheme can be discovered using patient inverse training confirmation tests from the widely accessible ICBHI 2017 Lung Sounds dataset.

An integrated mHealth system can provide personalised real-time feedback to patients to assess, educate and avoid common mistakes in proper medication use [19].

K. G. Fan et al, [9] proposed that modern clinical techniques can be used to implement a new method of Remote Patient Monitoring (RPM) to predict exacerbations and reduce relapses. Furthermore, an assessment scheme can be developed, and the evaluation method can be easily instigated.

A robust DL structure for auditory analysis aims to classify respiratory cycle abnormalities and detect diseases from respiratory records. Three substantial assistances to acoustic breath exploration can be

identified and tested using the ICBHI Breath Sound Benchmark dataset [12].

G. Altan et al, [6] proposed that the compound Machine Learning (ML) method can be used to prompt COPD exposure using multichannel lung sounds. FM numerical features and the Hilbert-Huang transform can be used to extract multichannel lung sounds.

G. Altan et al, [7] suggested that the Deep Extreme Learning Machine Classifier (Deep ELM) method can be grouped, which works as one of the most constant and fast DL algorithms. The proposed D-ELM model can handle the LuELM auto encoder to classify five COPD severities with high classification act proportions.

H. Sugimori et al, [8] aimed to progress a pre-processed or trained classifier using CT images to classify the initiative for Global Chronic Obstructive Lung Disease (GOLD). Additionally, a classification and assessment approach can be useful to decide the accuracy of the GOLD organisation with a confusion matrix.

F. Demir et al, [4] noted that using the ICBHI 2017 database to classify lung sounds can handle different model rates, noise and background sounds. First, the lung sound signal is developed into a spectrogram image by Time-Frequency (TF) modulation, and then the short-time Fourier transform (STFT) method can transform TF.

M. T. García-Ordás et al, [13] proposed that new labelled data and well-known oversampling methods can be employed after dataset type imbalances are realized. Breath sounds can be categorized into healthy, chronic and chronic diseases using CNN.

A. Abid et al, [1] proposed a single alveolar compartment model to specify the fractional compression of carbon dioxide during exhalation and to record them using time-based capnography. These can be deployed to assess respiratory parameters and associate them with the clinical status of patients with COPD.

The novel suggests that a Balanced Probability Distribution (BPD) algorithm can be implemented to develop transfer learning-based COPD. The algorithm can correlate event-based and feature-based displacements to improve the analysis accuracy of the model [15].

X. Lin et al, [20] suggested that an appropriate and valuable clinical decision support system can be used to identify patients with COPD in primary care settings. However, documentation of COPD patients is necessary for COPD preclusion and management.

A. Gökçen et al, [2] noted that they aim to develop a computer-aided diagnosis classification for intractable chronic COPD. It is necessary to reduce the treatment time by early diagnosis and analyze the abnormality in simple methods.

N. Syed et al, [14] aimed to validate the utility of ultrasound in assessing sleep-wake patterns in COPD patients compared to Polysomnography (PSG). Then, the point of indenture between PSG variables and actigraphy can be estimated using Bland-Altman plots.

Q. Xu et al, [16] mentions that COPD based on neural networks can be used as Traditional Chinese Medicine (TCM) and Intelligent Syndrome Differentiation (IS) methods.

Fang, Y et al, [5] proposed a fusion method based on extreme feature requirements that can be detected for COPD. The Maximum Dependency Features Rough Set (MDF-RS) algorithm works to extract the optimal arrangement of multidimensional features.

There are also a number of works done using CNN methods in literature applied in different fields [21-25].

2.1 Problematic of Declaration

- However, hospital Emergency Departments (EDs) are overcrowded with respiratory illnesses, resulting in poor quality attention.
- Asthma and COPD prevent respiratory disorders that adversely affect the patient's quality of life.
- COPD has five severity levels: life-threatening, mild, moderate, severe.
- Routes in the lungs become blocked due to increased air pollution in COPD.
- Comprehensive data analysis and actionable algorithms are essential to help clinicians more accurately diagnose COPD.

3. Proposed Methodology

In this section, a newly proposed method called DRCNN can be used to solve the problem of diagnosing chronic low respiratory disease. By these methods, the following models can be manipulated to get an estimate for image processing. We used the Kaggle Repository dataset to collect images for CLRD. Then, more methods can be used to evaluate the results using pre-processing as a first stage to reduce the image noise and detect the edges using a Gaussian filter. Next, we handle image segmentation to compute the binary image using the ITBS method and segment the regions. Evaluate the image values for each feature and threshold and select the feature using the chi-square test. Finally, classification by DRCNN can detect and classify chronic lower respiratory diseases better than the previous method.

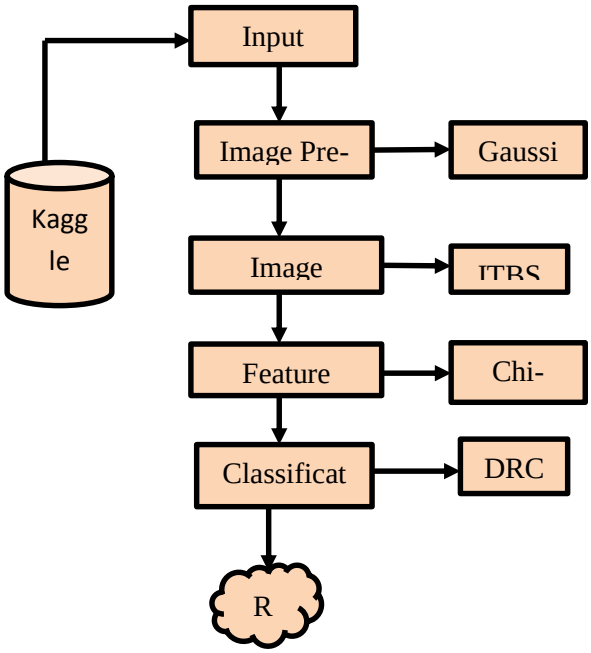

Figure 2. *The Proposed Architecture Diagram for CLDR*

In this section, the proposed architecture diagram for CLRD is well defined in Figure 2. The purpose of this map is to suggest a Kaggle repository for collecting images of respiratory disease. The images can be pre-processed by providing input images derived from them. Subsequent image segmentation is handled using the ITBS method, which enables image binary image counting and segmentation. After image segmentation, a chi-square test can be used to select the best features for these. Finally, the DRCNN method is implemented and classified as a better estimation than the previous methods.

3.1 Dataset Collection

In this section, CLRD is a crucial indicator of health and respiratory diseases by recommending a Kaggle repository to collect respiratory disease images. These include diseases that occur when a person breathes, directly affecting air movement, lung tissue changes, and lung secretions. For example, patients with obstructive disorders such as dyspnea, asthma, or COPD may experience respiratory symptoms. And these recordings were collected into 920 annotated recordings of varying lengths ranging from 10 seconds to 90 seconds and recordings from an additional 126 patients. Then, this data is captured with clear breathing and noiseless recordings simulating real-life situations.

Figure 3. *CLRD Architecture (https://getopt.com/2021/12/16/clrd/)*

Figure 3 in this section shows acute diseases affecting millions of people. Obstruction is irreversible in chronic bronchitis and emphysema but is in asthma.

3.2 Image Pre-Processing using Gaussian filter

In this section, the pre-processing steps necessary for the image analysis framework are selected and then used to enhance, reduce noise and detect edges for respiratory disease images. This analysis method can be found using a pre-processing model called a Gaussian filter. Pre-processing with a Gaussian filter works well for high-quality distortions. Because it blurs everything, removes unwanted noise and can be used to detect edges. However, the standard deviation was not always suitable for this segmentation task because the blurring effect of substantial respiratory disease images removes the edge of the image.

Algorithm

Input: Input images

Output: A pixel size of the grey value

Start

Step 1: The weights of the shape can be calculated using the Gaussian filter.

$$P_j(A,B) = J_j(A,B) * H_j(A,B;\delta_j) = \begin{cases} e_j(A,B) * H_j(A,B;\delta_j) \\ m_j(A,B) * H_j(A,B;\delta_j) \end{cases} \quad (1)$$

Step 2: Computes the steepness parameter under noisy signal.

$$H_j(A,B) = \frac{1}{2\pi\delta_j^2} exp\left(-\frac{A^2+B^2}{2\delta_j^2}\right) \quad (2)$$

Step 3: Evaluate the corresponding image window's grey value.

$$N_v(A,B) = \frac{1}{NXM}\sum_{j=-(n+1)/2}^{(n+1)/2}\sum_{i=-(m+1)/2}^{(m+1)/2} J_{(A,B)}(j,i) \quad (3)$$

Step 4: Calculate the difference between the current pixel and the window's grey value.

$$C(A,B) = \left|J(A,B) - N_{v(A,B)}\right| \quad (4)$$

Step 5: Evaluate the smoothness of equal pixels in a window.

$N_v(A,B) = \frac{1}{n \times m}[(n \times m)J(A,B)] = J(A,B)$ (5)

Step 6: Computes the size of a bounding sphere smoothening image

$\delta = C_j(A,B) = \left|J_j(A,B) - N_{vj(A,B)}\right|$ (6)

Step 7: Calculate the pixel scale by taking the mean grey value of the filter window and the current pixel's grey value.

$H_{(A,B),j}(j,i) = \frac{exp[-(j^2+i^2/2\delta^2{}_{(A,B),i})]}{\sum_{j=1}^{1}\sum_{i=1}^{1} H_{(A,B),j}(j,i)}\left|J_j(A,B) - N_{vj(A.B)}\right|$ (7)

Return H

Stop

Let's assume, δ – delta, A, B-current pixel size, $P_j(A,B)$-image signal, $H_j(A,B;\delta_j)$-two dimensional Gaussian kernel, $e_j(A,B)$-original signal, $m_j(A,B)$-noise signal, $n \times m$ –filter, v-window, $C_j(A,B)$-smooth image. In this category, the above filtering algorithm is a model based on Gaussian filtering which can be used to remove noise and detect and enhance image edges.

3.3 Image Threshold-Based Segmentation (ITBS)

In this section, we present an implementation of the ITBS procedure to find binary measures for the segmentation of chronic respiratory disease images. The image segmentation based on them can be used as foreground and background segmentation processes. And threshold segmentation is critical based on grey value information to extract the foreground. These are suitable for the segmentation of visible respiratory disease images with strong differences between them, in addition, segmentation regions and binary images can be calculated. In this category, calculate the overall grey-level variance of the image using probability density functions. (Equation 8).

$H(w) = H_1H_1(w) + H_2H_2(w)$ (8)

In this stage, Equation 9 calculates the probability that a pixel is either an object or a background pixel.

$H_1 + H_2 = 1$ (9)

Equation 10 is a segmenting image by classifying background pixels that have grayscale values greater than a certain threshold.

$F_1(Q) = \int_{-\infty}^{Q} H_2(w)c_w$ (10)

In this category, compute the probability of misclassifying the target point as a background point. Then, the overall error probability (Equations 11 & 12).

$F_2(Q) = \int_{T}^{\infty} H_1(w)c_w$ (11)

$H(Q) = H_2F_1(Q) + H_1F_2(Q)$ (12)

The pixel range can be estimated by calculating the average grayscale value of adjacent pixel values, as given in (Equation 13).

$Q_{op} = \frac{1}{(2n+1)(2m+1)}\sum_{A=-n}^{n}\sum_{B=-m}^{m} w(o+A, p+B)$ (13)

As shown in Equation 14, we obtain the edges within this block by considering the grey value variation of the pixels within a block.

$\sigma_{op}{}^2 = \frac{1}{(2n+1)(2m+1)}\sum_{A=-n}^{n}\sum_{B=-m}^{m}\left(w(o+A,p+B) - Q_{op}{}^2\right)$ (14)

Let's assume, H-pixel, w-random pixel value, $H_1(w)$& $H_2(w)$-pixel object and background, Q-Threshold, F-Error value, σ-variance, op-pixel grayscale value, Q_{op}-estimation of the threshold value, m&n- natural numbers. In this type, a pixel can be defined as a binary value if its grey value is below its threshold and the variance of the grey values of its neighbouring pixels is greater than a specified delta value and can also segment images.

3.4 Chi-square test

In this section, the best features for CLRD can be selected using the chi-square test to estimate the image values for each feature and threshold. The chi-square test is a test often implemented in feature selection to test the relationship between two categorical outcome attributes. A small chi-square value is obtained when the two features are independent and the resulting number is close to the expected value and, if the chi-square value is high, the assumption of uniqueness is invalid. Larger chi-square values indicate that the feature is responsive and more suitable for training the model. This chi-square test can calculate image values for features and ranges. Compute the sum of the observed and expected values given in Equation 15 in this section.

$A^2 = \sum(Z_a - F_a)^2 \,/\, F_a$ (15)

In this section, we estimate the sum of squares of the random variables as the sum of the stationary normal variables given by (Equation 16).

$a^2 = \sum wo^2$ (16)

In this type, the correlation strength for each feature is calculated separately by computing statistics (Equation 17).

$a^2 = \sum_{j=1}^{n}\frac{(F_j - z_j)^2}{F_j}$ (17)

Calculate the document limit for this fractional threshold value (equation 18).

$a^2(q,r) = \frac{M(xc-ry)^2}{(x+r)(y+c)(x+y)(r+c)}$ (18)

Let's assume, a-random value, j-feature class, w-standard variable, i-value, f-expected value, Σ-the sum of value, z-observed value, x and y-variant

frequency, q-frequency containing, r-class, M-quantity. In this type, using a large chi-square value to select the feature can indicate that the model is suitable for training, and the threshold values and range of an image can be calculated as the method.

3.5 Deep Recursive Convolutional Neural Network

In this respect, deep recursive convolutional neural networks (DRCNNs), a novel method, are widely implemented in applications for processing image data using DL techniques, especially for CLRD. This method works to train CLRD's highly efficient and deep networks. Besides controlling the application of DRCNN in the field of image processing, the application of DRCNN can also be extended to signal classification. A more powerful DRCNN can extract low- to high-order features of the input data to perform better, and then have multiple hidden layers that perform convolution and subsampling. A well-designed classification network generates features that segregate different classes, enabling competent classification. Canonical coefficients can be taken from odd samples and estimated for even samples to predict the stratified output. The approximate coefficients can be improved using detailed coefficients to update them. In terms of computational efficiency, maximum pooling and average pooling are the two most common choices used by DRCNN.

Algorithm

Input: image feature ranges

Output: Efficient feature layer a

Start

Step 1: The input signal to the split layer can be calculated by the model.

$$\zeta_i\,(a) = i(2a+1) \quad (19)$$

$$\gamma_1(a) = a(2a) \quad (20)$$

Step 2: calculate the output of the prediction layer and update the layer.

$$\zeta_2 = \zeta_1 - \varphi \circledast \gamma_1 \quad (21)$$

$$\gamma_2 = \gamma_1 + \mu \circledast \zeta \quad (22)$$

Step 3: The input signal used for the split layer is decomposed into odd and even sequences and evaluated.

$$\zeta_1^{(z)}(a) = i^{(z)}(2a+1) \quad (23)$$

$$\gamma_1^{(z)}(a) = i^{(z)}(2a) \quad (24)$$

Step 4: Calculate the output specification factors of the prediction layer followed by the splitting layer.

$$\zeta_2^{(z)} = h\left(\zeta_1^{(z)} - \varphi^{(z)} \circledast \gamma_1^{(z)}\right) \quad (25)$$

Step 5: Compute the approximate coefficients for the output.

$$\gamma_2^{(z)} = h\left(\gamma_1^{(z)} + \mu^{(z)} \circledast \zeta_2^{(z)}\right) \quad (26)$$

Step 6: Calculate the output approximation coefficient value.

$$\gamma_2^{(z)} = h\left(\gamma_1^{(z)} + \mu^{(z)} \circledast \zeta_2^{(z)}\right) \quad (27)$$

Step 7: Evaluate the maximum and average efficient features of pooling layers.

$$G_y = max\gamma_2^{(3)}(m) \quad (28)$$

Let assume, ζ-odd sample, γ-even sample, a-split layer, i-input value, h-function, G_y-feature, $\gamma_2^{(3)}$-output of the third update layer, $\circledast$-convoluctional layer, φ-phi, ζ-zeta, μ-Mu, $\mu^{(z)}$-weight vector update layer, φ and μ- weight vector, $\zeta_2^{(z)}$-output of the z predict layer, $\varphi^{(z)}$-weight vector of the z predict layer, $\gamma_2^{(z)}$-output of the z update layer, $\zeta_1^{(z)}(a)$- input to the z split layer. In this category, an enhanced learning method identifies the ability of coefficients to predict and update given layers to extract deeper representations of the input.

4. Result and Discussion

This section aims to obtain and implement the average accuracy of these using the jupyter toolbox using the Python language to achieve accurate results using image processing to determine the accuracy of chronic low respiratory disease.

Table 1. *Simulation Parameter*

Simulation Model	Variables
Dataset Name	Kaggle Repository
No of Dataset	480
Tool	jupyter
Language	Python
Training	250
Testing	110

As shown in Table 1, the correct testing and training estimation for these can be achieved through Python using the Jupyter tool to get their accuracy in testing and training time based on simulation parameters.

4.1 Evaluation of Matrix

This section evaluates model performance using separate metrics such as training and test set accuracy. The metrics considered in this work include precision, accuracy, recall, sensitivity and specificity for estimating their averages. Additionally, samples can be interpreted as true positive, true negative, false negative and false positive. In this category, the number of cases can be implemented to identify the accuracy of the introduced models and provide correct predictions

as illustrated in Table 2. TP can represent TN, FP, and FN to represent the total number of full cases.

Table 2. *Evaluation of the Model*

Model	**configuration**
Precision	$\frac{T_P}{T_P+F_P}$
Recall	$\frac{T_P}{T_P+F_N}$
Sensitivity	$\frac{T_P}{T_P+F_N}+100\%$
Specificity	$\frac{T_N}{T_N+F_P}+100\%$
Accuracy	$\frac{Y_{True}}{Total}+100\%$

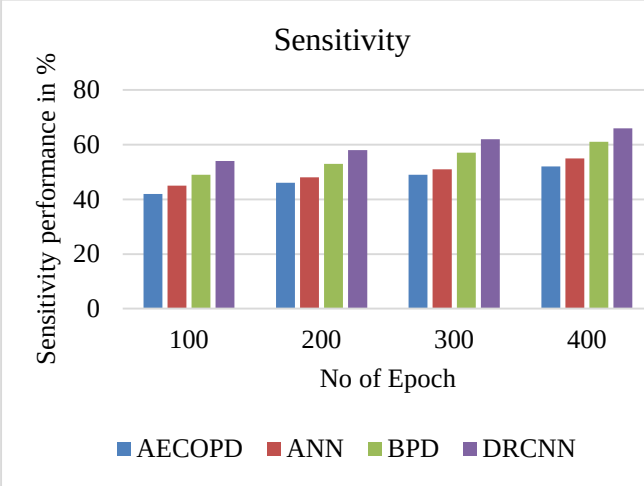

Figure 4. *Performance of the Sensitivity*

In this section, they can be quantified using well-defined models to detect chronic respiratory disease accuracy, as shown in Figure 4. Furthermore, the three methods presented in the literature analysis, AECOPD, ANN and BPD, have been found to have less accuracy during testing. Comparing the proposed method DRCNN with the three methods presented in the analysis of chronic low respiratory disease accuracy, their accuracy reaches a higher level. In this section, we use well-implemented models to achieve chronic respiratory disease accuracy introduced in Figure 5 to obtain their accuracy. Then, given in the literature analysis and tested with three methods such as BPD, ANN and AECOPD, the measurement of specific performance has less accuracy. The specificity performance in the analysis of chronic low respiratory disease accuracy is numerically increased by 70% of the proposed method DRCNN compared to the other three methods. This section aims to monitor the accuracy of chronic respiratory disease using recall analysis, as illustrated in Figure 6. Then, the accuracy of three methods such as BPD, AECOPD and ANN, derived from them, suggested the literature analysis to get the average rating on recall performance and obtained the

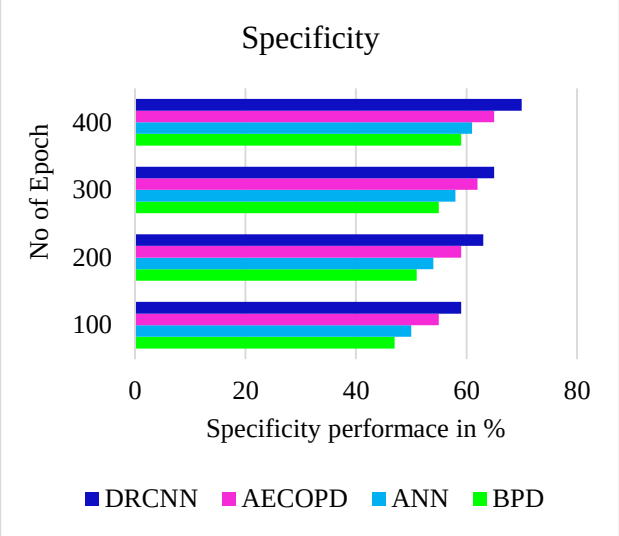

Figure 5. *Performance of the Specificity*

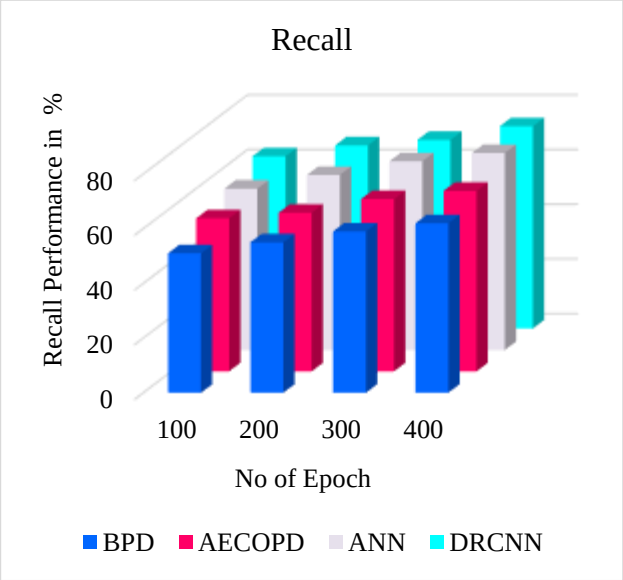

Figure 6. *Performance of the Recall*

number of minimum accuracy. Also, the accuracy of all three methods obtained from the literature analysis has increased to 76% compared to the newly introduced DRCNN methods. As illustrated in Figure 7, a well-defined systematic performance analysis can be used to obtain accuracy for chronic respiratory disease. After that, the accuracy for respiratory disease can be obtained using three methods, ANN, BPD and AECOPD, presented from the literature analysis for accuracy. Then comparing the methods obtained through literature analysis with the newly proposed methods DRCNN for respiratory disease, their accuracy increased significantly to 82%. The foremost objective of this section is to find the correct accuracy for chronic disease from literature analysis; all three methods used have less than 56% accuracy. However, comparing these three methods with the newly used DRCNN proposed method, their accuracy has increased to 89%, as illustrated in Figure 8.

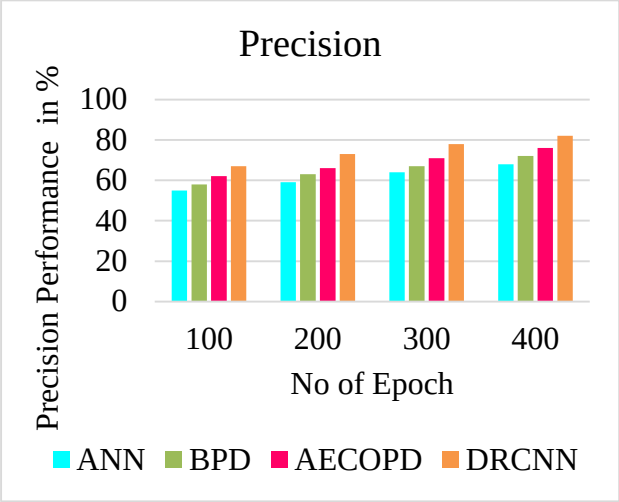

Figure 7. *Performance of the Precision*

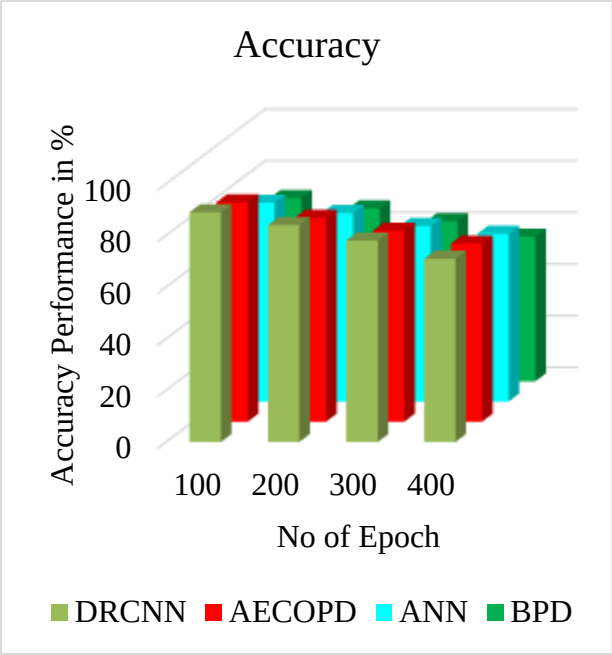

Figure 8. *Analysis of the Accuracy*

5. Conclusion

In this study, we proposed a method for a DL-based DRCNN method to help medical professionals diagnose CLRD. In the experiments conducted, firstly, we collected images for CLRD using a Kaggle repository, and then based on these the results obtained in the following framework can be used to obtain an estimate. As a first step, we use a pre-processing method to detect the noise and edges of the images. Then the method can be followed by image segmentation using ITBS based segmentation method to count the binary image and segment it. Next, we introduced the chi-square test to find the image values for each feature and threshold. Finally, the proposed new DRCNN method can be used to classify the accurate value for CLRD. In addition, CLRD can be detected by multi-level measures such as sensitivity, specificity, precision, accuracy and recall of the set to determine the exact accuracy of the method. The accuracy of the three methods introduced through literature analysis for diagnosing chronic respiratory disease increased to 89% when compared with the proposed DRCNN method. Therefore it is concluded that the DRCNN method can predict the survival of patients suffering from chronic lower respiratory diseases with the help of a DL model.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of 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
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