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Moth Flame Optimization with Long Short-Term Memory for Pneumonia Detection and Classification

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Abstract

Pneumonia is a life-threatening lung infection so it requires initial recognition and exact classification in order to simplify quick medical intervention. This research addresses high-risk challenge of pneumonia analysis as well as classification by connecting highly-advanced technologies in medical imaging and machine learning (ML). This paper develops the Moth Flame Optimization with Long Short-Term Memory for Pneumonia Detection and Classification (MFOLSTM-PDC) model on Chest X-rays (CXR). Primary, we use a Wiener filter to improve the excellence of CXR images, decreasing noise and enhancing prominence of serious facts. And then, we remove high-level features from pre-processed images employing a DenseNet method. The detection stage employs an LSTM system which is a sort of recurrent neural network (RNN) that is suitable for consecutive data analysis. The LSTM is mainly trained in order to identify patterns and relations within removed features and then differentiate between pneumonia and non-pneumonia cases. We use MFO for parameter tuning to further improve the performance of the detection method. MFO is a nature-inspired optimization technique that perfects hyper-parameters of the LSTM method that guarantee optimum performance. The developed technique is verified on a huge dataset of CXR images by validating its efficiency in pneumonia recognition and classification. This complete procedure signifies a promising method for improvement of strong and exact pneumonia analysis systems with probable applications in medical settings to help healthcare experts in making decisions on time.

Keywords: Chest X-ray; Moth flame optimization; Deep learning; Long short-term memory; Parameter tuning

1. Introduction

Pneumonia is the leading causes of death among old age populace as well as children all over the world. It is mainly caused by bacteria, viruses or other germs [1]. Pneumonia results in infection in the lungs that can be life-threatening if not analysed in early stage. One of the essential pneumonia diagnosis techniques is Chest X-ray. But, professional knowledge as well as experience is needed to read X-ray images cautiously [2]. The procedure of pneumonia recognition by observing X-ray imageries can be less accurate and time-consuming. The main purpose is that some other medical circumstances such as excess fluid, lung cancer and much more can similarly show related opacities in images [3]. So, precise evaluation of images is extremely required. The influence of computing is well-known and proposing an identification technique for the discovery pneumonia origins in clinical images can aid in exact and enhanced understanding of X-ray images. X-ray image examination is measured as a crucial and tiresome tasks for experts of radiology [4]. Therefore, many researchers have developed numerous computer techniques in order to analyse X-ray images as well as computer assisted identification tools have been presented to offer an understanding of X-ray images [5]. Moreover, these tools are not capable of afford sufficient information to aid doctors in making decisions. Machine learning (ML) is one of the essential techniques in an artificial intelligence (AI) field [6].

Deep learning (DL) is also another significant AI tool, which plays a vital part in resolving numerous difficult computer vision issues. DL methods particularly convolutional neural networks (CNNs) are employed widely for numerous image detection issues [7]. However, these models execute only when it is offered with a huge extent of dataset. For bio-medical image detection issues, this huge range of labeled data is very challenging in order to obtain due to it needs that medical specialists categorize all images, which is a costly as well as inefficient task. Transfer learning (TL) is a function about to overcome this difficulty [8]. To solve a problem, this technique involves a lesser database [9], a method skilled on a huge database is re-used and then network weights defined in this model can be functional [10]. CNN methods are trained with a huge database like ImageNet that contains above 14 million images and is often utilized for biomedical image detection tasks.

Akgundogdu [11] used ML techniques for assessing X-ray images. The analyses of pneumonia can be categorized with an established ML model by employing CXR images. This model primarily utilizes 2D discrete wavelet transform for removing features from images. Additionally, the RF technique is employed for detection method. A 10-fold cross-validation method oppressed for assessing technique. In [12], the author mainly focused on planning a system that will help by sorting of CXR medical imageries into regular and irregular. To attain this, ML and CNN models are used to enhance correctness and efficiency. The authors proposed DL for recognition task that can be trained with different images by multi-stages of pre-processing according to this research. Abubeker and Baskar [13] directed to creation an original and effective multi-class ML technique to classify as well as detect CXR images on GPU. The authors chiefly employed a regular augmentation by positional alteration function to the unique database for growing the size of samples as well as helping upcoming TL. Chandra and Verma [14] proposed a model for spontaneous recognition of pneumonia on segmented lungs employing the ML method. This research focuses on pixels in lungs segmented ROI, which advance donate toward pneumonia analysis than nearby regions, so features of lungs segmented ROI inadequate extent has been removed.

This paper develops the Moth Flame Optimization with Long Short-Term Memory for Pneumonia Detection and Classification (MFOLSTM-PDC) model on CXR. Primary, we use a Wiener filter to improve the excellence of CXR images, decreasing noise and enhancing prominence of serious facts. And then, we remove high-level features from pre-processed images employing a DenseNet method. The detection stage employs an LSTM system which is a sort of recurrent neural network (RNN) that is suitable for consecutive data analysis. We use MFO for parameter tuning to further improve the effectiveness of the detection system. The developed method is verified on a huge dataset of CXR images by validating its efficiency in pneumonia recognition and classification.

2. The proposed model

In this study, we have designed and expansion of MFOLSTM-PDC approach for pneumonia detection and classification by combining advanced techniques in preprocessing, feature extraction, classification, and parameter tuning. Fig. 1 represents the workflow of MFOLSTM-PDC algorithm.

2.1. Preprocessing

Initially, we use a Wiener filter (WF) to enhance quality of CXR images by decreasing noise as well as enhancing the discernibility of dangerous facts. In pneumonia classification, the pre-processing step is a WF that plays a vital part in improving superiority of medical imaging data, naturally CXR [15]. By successfully decreasing noise as well as filtering image clarity, WF enhances the analytic possible of these images. This procedure of noise reduction permits healthcare experts and ML techniques to exactly recognize pathological features and irregularities. Therefore, contributing to primary and accurate pneumonia detection is vital for medical intervention on time and enhanced patient results.

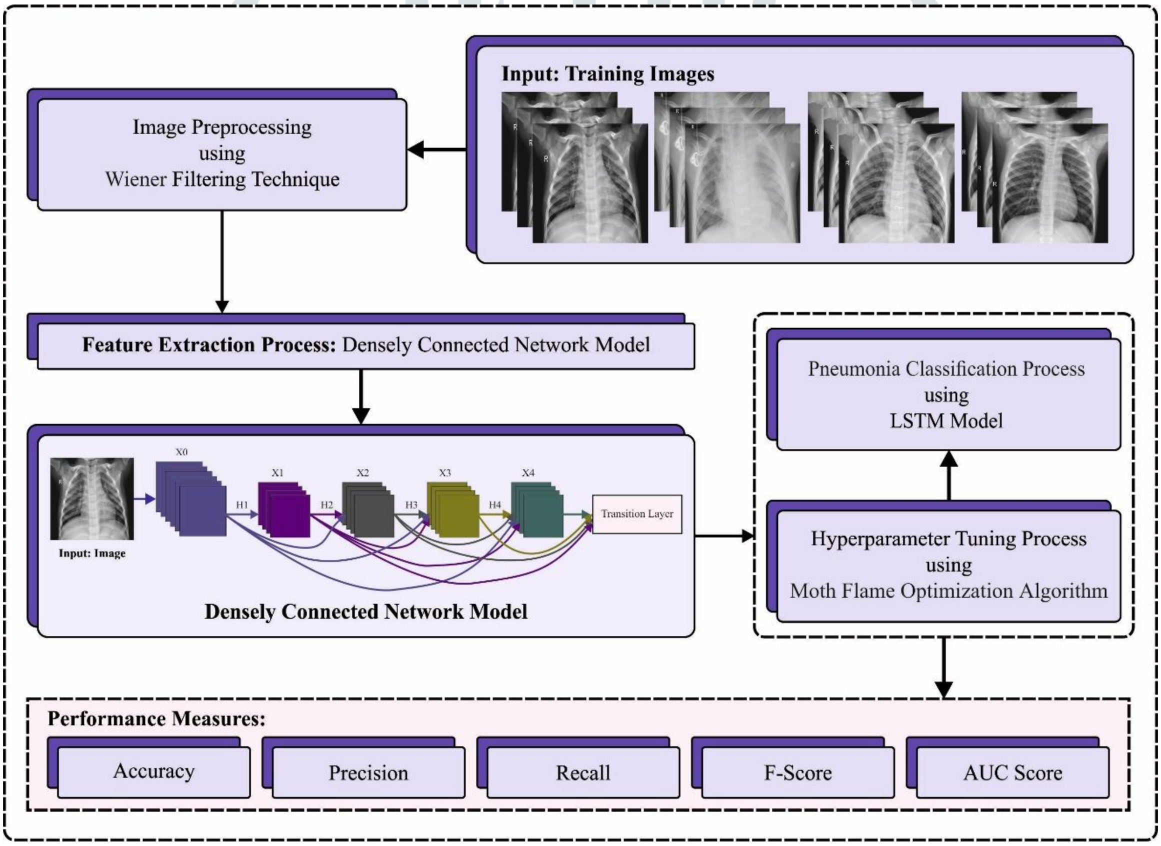

Fig. 1. Workflow of MFOLSTM-PDC approach

2.2. Feature extraction

Next, we extract high-level features from the preprocessed images using a DenseNet model. Feature extraction (FE) using the DenseNet method is dominant and effective in computer vision as well as image analysis [16]. DenseNet framework is considered by its compactly connected layers, which simplify removal of useful features from difficult and full images. When compared to CNN, feature maps are fixed consecutively, and DenseNet connections among layers are thick, warranting that each layer gets straight and plentiful data from previous layers. The DenseNet efficiency stops from its aptitude for capturing low and high-level features throughout the network. Generating a feature hierarchy permits the technique to understand difficult patterns and relations within the data. This FE technique is valuable in applications like pneumonia or image classification, where detailed and hierarchical features removed by DenseNet contribute to enhanced accuracy and sturdiness. By integrating these feature representations into diagnosis, DenseNet authorizes DL techniques in order to separate restrained nuances and increase the exactness of tasks such as disease recognition that lead to get actual healthcare diagnostics and mediations.

2.3. Classification using LSTM model

For the classification process, the LSTM model is utilized. LSTM is a technique that is capable to generate a technique with long-term memory at a similar time [17]; it could be disremember insignificant data in training data. LSTM displays has various dissimilarities from traditional RNNs:

1. LSTM has dual kinds of activation functions: The primary is $tanh$, which is more usual. Its output standards range from -1 to 1. This work adjusts system data movement and evades explosion gradient phenomena. The $tanh$ function is determined as follows:

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{1}$$

Next activation work is the sigmoid function. Its output standards range from -1 to 1 for permitting unrelated data to be rejected by neural networks. The following expression is the sigmoid activation function:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

2. Hidden state (HS) and cell state (CS): HS in traditional RNN framework has binary procedures like those that it is employed as a memory of the system and as an output of the network. Additionally, LSTM systems implement a CS. The HS in RNN aids as a short-term working memory but CS is utilized as a long-term memory in LSTM to store vital information from previous.

Gates: The status values in LSTM can be altered over devices known as gates. LSTM has 4 gates they are input gate i, candidate gate c, forget gate f and output gate 0 which is shown in

2.4. Parameter tuning using the MFO model

To further enhance the performance of the classification model, we employ MFO for parameter tuning. Mirjalili introduced MFO in 2015 as a naturally inspired optimizer technique which simulate the activity of individual in a search agents (swarm of moths) that have exclusive navigation method [18]. In this work, the candidate solution is considered as search agent. To model how individual moves in spiral, the m-by-d matrix such as M is utilized, where m denotes the search agent count and d dimension counter. There is an array for each entity to store the objective function values as m-by-one matrix like OM.

The flame that can be described in m-by-d matrix named F, is an crucial part of these algorithms. Note that there is a technique for storing fitness value F as OF in an array. While applying the MFO technique, F is considered as best location of M in the search range. Each search agent's location is adapted to mathematically model this action using Eq. (3):

$$M_i = S(M_i, F_j), \tag{3}$$

Now M_i denotes the i^{th} search agent and F_j shows the j^{th} optimum location, and S represents the logarithmic spiral function that can be updated by Eq. (4):

$$S(M_i, F_j) = D_i e^{cr} \cos(2\pi r) + F_j, \tag{4}$$

Here r denotes the random integer within $[-1,1]$, c refers to the constant that describes the shape of logarithmic spiral then, D_i factor denotes the distance of i^{th} searching agent for j^{th} flames that can be evaluated by the following expression:

$$D_i = |F_j - M_i|. \tag{5}$$

M uses one of F to modify the position, and an adaptive model for the number of F is shown below:

$$flame\ no. = round\left(N - \frac{t(N-1)}{T}\right), \tag{6}$$

Here the existing iteration number is t, the maximal amount of flames is N, and the maximal iteration count is T.

3. Result analysis and discussion

The pneumonia detection results of the MFOLSTM-PDC technique can be tested employing a dataset from Kaggle repo5sitory [19]. Fig. 2 illustrates the sample normal and pneumonia images.

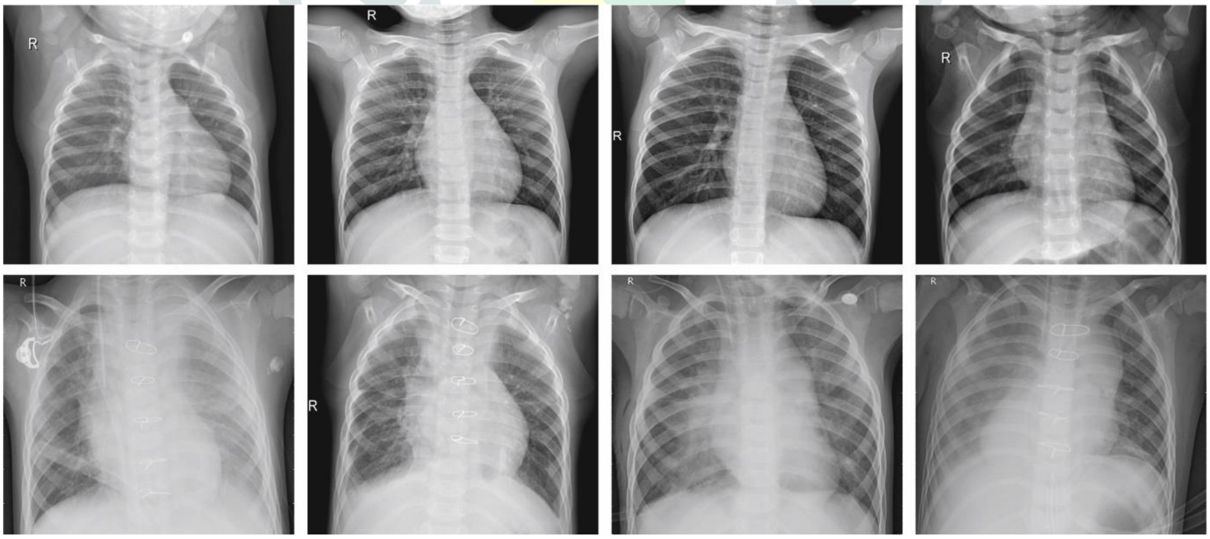

Fig. 2. a) Normal b) Pneumonia

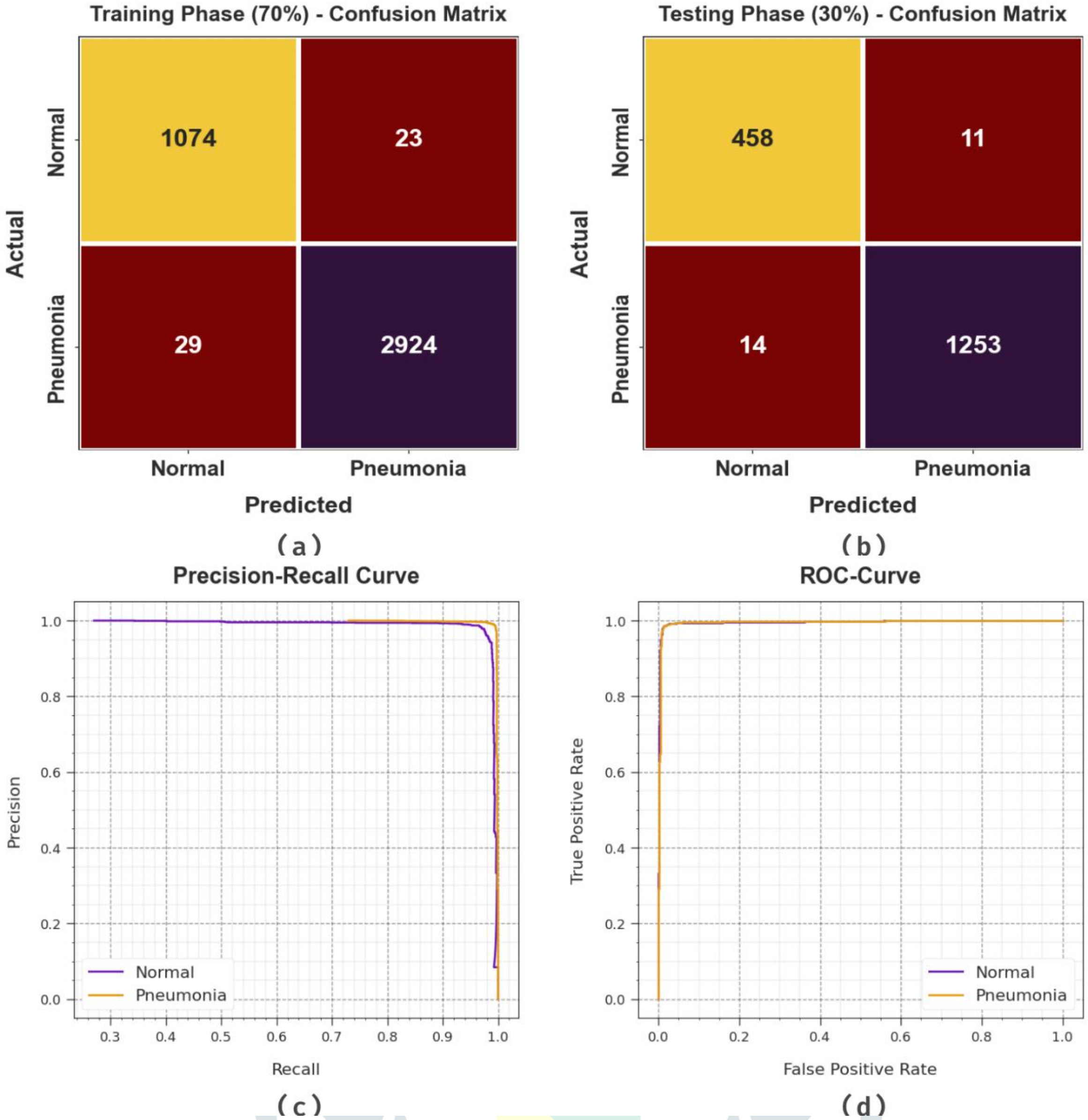

Fig. 3. (a-b) Confusion matrices of TR/TS phase of 70% and 30% and (c-d) PR curve and ROC curve

Fig. 3 shows the classifier analysis of the MFOLSTM-PDC system at test database. Figs. 3a-3b represents the confusion matrix provided by the MFOLSTM-PDC technique with 70:30 of TR Phase/TS Phase. The figure exhibits that the MFOLSTM-PDC model is appropriately recognized and categorized with normal and pneumonia classes. Moreover, Fig. 3c illustrates the PR performances of the MFOLSTM-PDC system. Then, this figure shows that the MFOLSTM-PDC methodology gets exceptional PR performance with two classes. Besides, Fig. 3d exhibits the ROC outcome of the MFOLSTM-PDC methodology. The figure indicated that the MFOLSTM-PDC system accelerates efficient outcomes with greater ROC values with each class.

The pneumonia recognition results under 70:30 of TR phase/TS phase is stated in Table 1. The simulation value show that the MFOLSTM-PDC methodology properly recognizes and categories two classes. For instance, on 70% of TR phase, the MFOLSTM-PDC technique attains an average $accu_y$, $prec_n$, $reca_l$, F_{score}, and AUC_{score} of 98.72%, 98.30%, 98.46%, 98.38%, and 98.46% respectively. In addition, with 30% of TS phase, the MFOLSTM-PDC system achieves an average $accu_y$, $prec_n$, $reca_l$, F_{score}, and AUC_{score} of 98.56%, 98.08%, 98.27%, 98.18%, and 98.27% correspondingly.

Table 1 pneumonia recognition analysis of MFOLSTM-PDC system with 70:30 of TR phase/TS phase

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	AUC_{score}
TR Phase (70%)					
Normal	98.72	97.37	97.90	97.64	98.46
Pneumonia	98.72	99.22	99.02	99.12	98.46
Average	**98.72**	**98.30**	**98.46**	**98.38**	**98.46**
TS Phase (30%)					
Normal	98.56	97.03	97.65	97.34	98.27
Pneumonia	98.56	99.13	98.90	99.01	98.27
Average	**98.56**	**98.08**	**98.27**	**98.18**	**98.27**

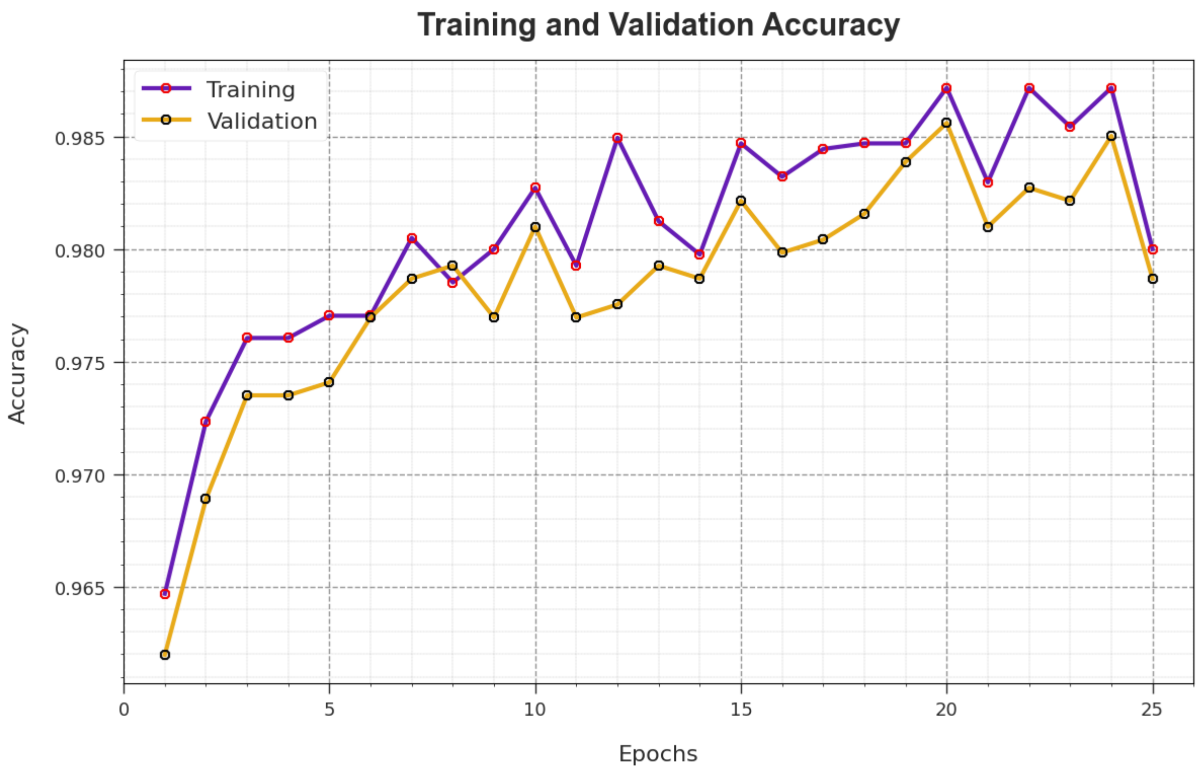

Fig. 4. $Accu_y$ curve of MFOLSTM-PDC approach

To determine the effectiveness of the MFOLSTM-PDC algorithm, we are created $accu_y$ curves for the training (TR) as well as testing (TS) phases as shown in Fig. 4. These curves gives valued insights for the model's ability and learning expansion in generalization. As we increase the number of epochs, an apparent improvement in TR and TS $accu_y$curves can be evident. This enrichment exhibits the model's potential to greater identify patterns along with both the TS /TR datasets.

Finally, the enhanced performance of the MFOLSTM-PDC technique can be ensured by a comparison study in Table 2 and Fig. 5 [20]. The obtained outcome exhibited that the MFOLSTM-PDC methodology is enhanced performances with other models. Based on $accu_y$, the MFOLSTM-PDC technique has attained higher $accu_y$ value of 98.72% while the Visualization-CNN, ADFL-mRMR, X-ray Images-NN, DPC X-Rat-Dl, CNN, and Chest Xray-DTL approaches have obtained lower $accu_y$ values of 96.20%, 96.84%, 94.40%, 84.50%, 98%, and 98.43% respectively.

Table 2 $Accu_y$ analysis of IMFOHDL-ID model with other systems

Model	Accuracy
Visualization-CNN	96.20
ADFL-mRMR	96.84
X-ray Images-NN	94.40
DPC X-Rat-Dl	84.50
CNN Model	98.00
Chest Xray-DTL	98.43
MFOLSTM-PDC	98.72

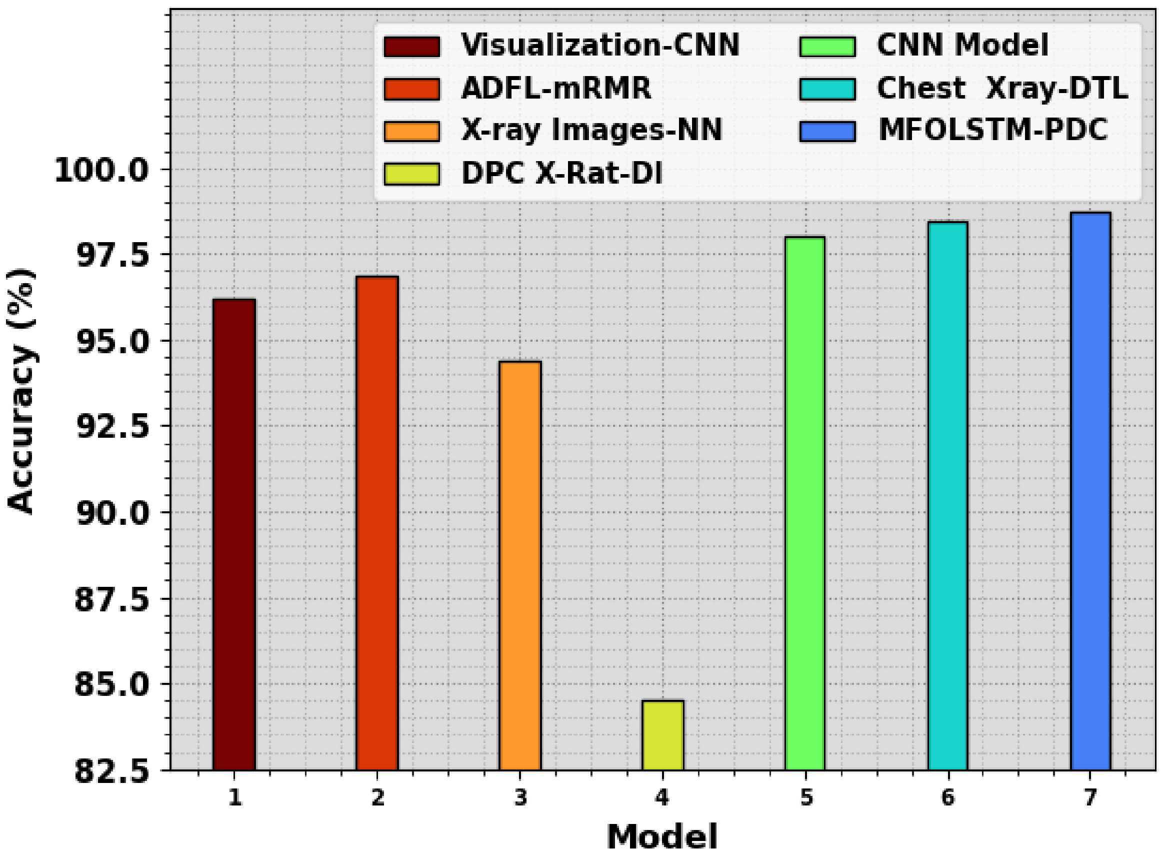

Fig. 5. $Accu_y$ analysis of MFOLSTM-PDC system compared with existing methods

4. Conclusion

In this study, we have designed and development of MFOLSTM-PDC approach for pneumonia detection and classification by combining advanced techniques in preprocessing, feature extraction, classification, and parameter tuning. Primary, we use a WF to improve the excellence of CXR images, decreasing noise and enhancing prominence of serious facts. And then, we remove high-level features from pre-processed images employing a DenseNet method. The detection stage employs an LSTM system which is a sort of RNN that is suitable for consecutive data analysis. We use MFO for parameter tuning to further improve the performance of the detection method. The developed technique is verified on a huge dataset of CXR images by validating its efficiency in pneumonia recognition and classification. This complete procedure signifies a promising method for improvement of strong and exact pneumonia analysis systems with probable applications in medical settings to help healthcare experts in making decisions on time.

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