IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received October 11, 2021, accepted October 22, 2021, date of publication October 27, 2021, date of current version November 8, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3123782

A Novel Method for Multivariant Pneumonia Classification Based on Hybrid CNN-PCA Based Feature Extraction Using Extreme Learning Machine With CXR Images

MD. NAHIDUZZAMAN[1], MD. OMAER FARUQ GONI[1], MD. SHAMIM ANOWER[2], (Member, IEEE), MD. ROBIUL ISLAM[1], MOMINUL AHSAN[3], JULFIKAR HAIDER[4], SARAVANAKUMAR GURUSAMY[5], (Member, IEEE), RAKIBUL HASSAN[1], AND MD. RAKIBUL ISLAM[1]

[1]Department of Electrical and Computer Engineering, Rajshahi University of Engineering and Technology, Rajshahi 6204, Bangladesh
[2]Department of Electrical and Electronic Engineering, Rajshahi University of Engineering and Technology, Rajshahi 6204, Bangladesh
[3]Department of Computer Science, University of York, Heslington, York YO10 5GH, U.K.
[4]Department of Engineering, Manchester Metropolitan University, Manchester M1 5GD, U.K.
[5]Department of Electrical and Electronics Technology, Ethiopian Technical University, Addis Ababa 190310, Ethiopia

Corresponding author: Saravanakumar Gurusamy (saravanakumar.gurusamy@etu.edu.et)

ABSTRACT In this era of COVID19, proper diagnosis and treatment of pneumonia are very important. Chest X-Ray (CXR) image analysis plays a vital role in the reliable diagnosis of pneumonia. An experienced radiologist is required for this. However, even for an experienced radiographer, it is quite challenging and time-consuming to diagnose accurately due to the fuzziness of CXR images. Also, identification can be erroneous due to the involvement of human judgement. Hence, an authentic and automated system can play an important role here. In this era of cutting-edge technology, deep learning (DL) is highly used in every sector. There are several existing methods to diagnose pneumonia but they have accuracy problems. In this study, an automatic pneumonia detection system has been proposed by applying the extreme learning machine (ELM) on the Kaggle CXR images (Pneumonia). Three models have been studied: classification using extreme learning machine (ELM), ELM with a hybrid convolutional neural network-principal component analysis (CNN-PCA) based feature extraction, and CNN-PCA-ELM with the CXR images which are contrast-enhanced by contrast limited adaptive histogram equalization (CLAHE). Among these three proposed methods, the final model provides an optimistic result. It achieves the recall score of 98% and accuracy score of 98.32% for multiclass pneumonia classification. On the other hand, a binary classification achieves 100% recall and 99.83% accuracy. The proposed method also outperforms the existing methods. The outcome has been compared using several benchmarks that include accuracy, precision, recall, etc.

INDEX TERMS Chest X-Ray (CXR), convolutional neural network (CNN), contrast limited adaptive histogram equalization (CLAHE), extreme learning machine (ELM), feature extraction, principal component analysis (PCA), pneumonia.

I. INTRODUCTION

The inflammation of the lung due to the virus, bacteria, or fungi attack causes reduced oxygen level in the bloodstream and chest pain when breathing. It fills the alveoli of the lung with fluid or pus. It ranges from mild to severe and requires patients to be treated in the hospital. Symptoms like pain with breathing, fever, shivering, cough with pus, lack of appetite indicate pneumonia. In recent times, these symptoms also indicate COVID19. Therefore, it is a crucial

The associate editor coordinating the review of this manuscript and approving it for publication was Chao Tong.

visit to the doctor to identify which one is among pneumonia, COVID19, and normal cough. Based on the identification, it should require rapid treatment. People of any age can be affected by pneumonia, but children aged less than five and older people more than 65 years are more likely to be affected by pneumonia due to their weak immune systems. Every year, many people die due to a lack of proper treatment because the patient either does not take it seriously or is identified late. It is the prime reason behind the death of children aged less than five years on a global scale and the death rate is around 95% in developing countries [1]. In 2015 around 17,850 (15%) died from pneumonia among the total deaths of 119,000 children who are aged five years or less in Bangladesh [2]. Around three children die every hour, 67 per day and 24,300 per year in Bangladesh [3].

Pneumonia is diagnosed using CXR images. It shows the spot of the infection and the extent to which the virus infected the lung. A radiologist investigates CXR images to identify the presence of pneumonia or any other kinds of lung diseases. However, for a human to diagnose and correctly recognize pneumonia using the CXR images is a time-consuming and quite challenging task. The CXR images are sometimes unclear and fuzzy, which drives an erroneous detection. To reduce the number of death, a trustworthy diagnosis system is required.

In this modern technological era, machine learning (ML) performs a great role in automatically detecting diseases such as heart diseases, breast cancer, and brain cancer. CXR images can be used to train a ML model for developing a trustworthy automatic pneumonia detection system that will reduce the workload of radiologists. The novel contribution in this work:

- Extreme learning machine (ELM) has been used to reduce training time cost as it has no iterative tuning parameter instead of traditional deep learning algorithms.
- Image contrast has been enhanced by applying contrast limited adaptive histogram equalization (CLAHE) to achieve better accuracy.
- Features have been extracted using new hybrid convolutional neural network - principal component analysis (CNN-PCA) to get discriminant features and reduce the model complexity. CNN has been used to extract features from raw data, which PCA follows.
- Multiclass (viral pneumonia, bacterial pneumonia, and normal) and binary (pneumonia and normal) class classification has been performed using different machine learning approaches such as CNN, CNN-ELM, CNN-PCA-ELM, and CLAHE-CNN- PCA-ELM.

The next section II describes recent research in this field. The proposed methodology of the model is described in section III. Section IV presents the results obtained from the ML model, which are compared to the findings of other recent studies. Finally, in section V, the key conclusions are presented.

II. LITERATURE REVIEW

Jain *et al.* [4] analyzed six models that include 2 CNN models (Model 1, Model 2), VGG16, VGG19, ResNet50, and Inception-v3 to spot pneumonia using CXR images. Model 2, consisting of 3 convolutions and two dense layers, achieved the highest validation accuracy and recall of 92.31% and 98%, respectively. Chouhan *et al.* [5] proposed an ensemble model based on transfer learning for detecting pneumonia that achieved the test accuracy and recall of 96.4% and 99.62%, respectively. The ensemble model consists of AlexNet, DenseNet121, InceptionV3, resNet18, and GoogLeNet neural networks. Rahman *et al.* [6] performed three experiments, with one of them is pneumonia classification. They trained four pre-trained models, including AlexNet, ResNet18, DenseNet201, and SqueezeNet, to carry out the experiments for detecting pneumonia using the CXR images. Among them, DenseNet201 achieved the highest accuracy of 98% during the pneumonia classification. To train the models, images were resized and normalized according to the requirements of the transfer learning models. Image augmentation techniques (Rotation, Scaling, and Translation) were also performed. Wu *et al.* [7] proposed a hybrid model named ACNN-RF for pneumonia detection that achieved 97% accuracy. The full study can be divided into three steps. In the first step, an adaptive median filtering technique has been used to remove noise from the CXR images. In the second step, a CNN model was developed to extract features. And, in the final steps, a Random Forest (RF) model was trained with the extracted features for the detection process.

Mittal *et al.* [8] used Integration of convolutions with capsules (ICC), Ensemble of convolutions with capsules (ECC), and EnCC (where n = 3, 4, 8, 16) on Mendeley CXR image dataset for pneumonia detection. Among them, E4CC achieved the optimal accuracy of 96.36%. Sarker *et al.* utilized bilateral filtering for noise reduction and enhanced the contrast of the CXR images using CLAHE [9]. Using a separable convolution technique and the benefits of deep residual learning, their suggested model reached a classification accuracy of 98.82%. Abin *et al.* proposed a dehazing approach for the detection of pneumonia from the CXR images [10]. They removed the noise and improved the contrast of the CXR images using CLAHE. Ayan *et al.* [11] used transfer learning-based model Xception and VGG16 for pneumonia classification. VGG16 achieved 87% accuracy. Sharma *et al.* [12] used two CNN models, CNN with dropout layer and CNN without dropout layer, for the detection purposes. They also used different augmentation techniques to avoid overfitting. The model with augmentation and dropout together achieved 90.68% accuracy. Heidari *et al.* [13] used transfer learning-based model VGG16 to detect COVID19 based pneumonia using X-ray images and achieved 98.8% accuracy. Liang and Zheng [14] used a combination of residual thought and dilated convolution to establish a system that can identify the pneumonia. The proposed method achieved an f1 score of 92.7%.

Ibrahim *et al.* [15] proposed AlexNet based pneumonia classification. The pneumonia dataset contains four classes: COVID 19, viral pneumonia, bacterial pneumonia, and normal pneumonia. They trained the model for different combinations such as 2-class, 3-class, and 4-class classifications. Ibrahim *et al.* [16] performed multiclass classification that included COVID19, pneumonia, and lung cancer. They used both the CXR and CT scan images to train four models for classification, including VGG19-CNN, ResNet152V2, ResNet152V2 + Gated Recurrent Unit (GRU), and ResNet152V2 + Bidirectional GRU (Bi-GRU).

Lahoura *et al.* [17] proposed a breast cancer diagnosis system which was a cloud computing-based framework using ELM, and performed a comparison with different state-of-art models. ELM was shown a favorable result. Khan *et al.* [18] proposed a deep extreme learning machine (DELM) method for COVID19 detection, which achieved 97.59% accuracy.

Many researchers have investigated pneumonia detection and have presented many machine learning approaches to address this issue. Some of these articles have presented lower true positives rates, which are not acceptable in the case of detecting pneumonia-affected patients. Again, most articles only consider binary class; it is also important to distinguish between bacterial and viral pneumonia. The majority of approaches failed to deliver the high accuracy required, particularly in the 3-class scenarios. The existing methods consist of heavyweight models such as VGG, AlexNet, DenseNet121, Inception, ResNet, etc., which have a large number of tunable parameters, and hence they require a longer training time and higher computational power. In contrast, the proposed model consists of a simple CNN as a feature extractor. ELM has been used to classify binary and multiclass pneumonia as a classifier, and this does not have any iterative tuning parameter. This approach saves time for the training operation and reduces the classifier complexity.

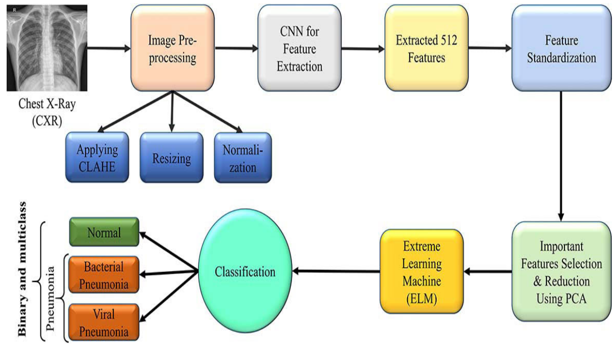

FIGURE 1. Proposed methodology for detecting pneumonia from CXR images.

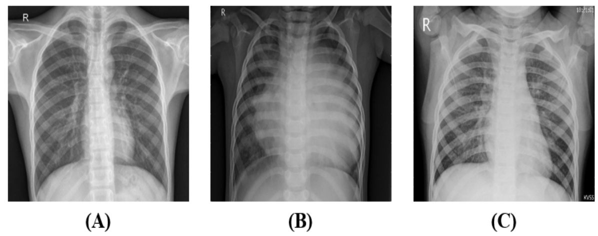

FIGURE 2. Sample images of (A) normal, (B) bacterial pneumonia, and (c) viral pneumonia.

TABLE 1. Details of the dataset.

Type	No. of X-Ray Images
Normal	1583
Bacterial Pneumonia	2779
Viral Pneumonia	1495
Total	5857

III. METHODOLOGY

Data scientists have used several ML and DL architecture to predict different life-threatening diseases, such as COVID19, pneumonia, heart diseases, etc., using medical images in the last few decades. This study has attempted to correctly identify pneumonia from CXR images by combining the benefits from both the DL and ML algorithms.

First of all, the CXR images of pneumonia patients have been collected and subsequently enhanced the quality of the images using CLAHE. Since the images are different in size, all the images are resized into 224×224. The last part of the image pre-processing has been performed by normalization. Then, a novel CNN model with six convolution layers has been designed for extracting the most discriminant features from the pre-processed images. Furthermore, the features have been standardized before PCA. Then PCA has been used for further selecting the essential features by maximizing the variance and also reduced the features that are not absolutely necessary [19]. Finally, an (ELM) model has been designed for the correct classification of the pneumonia patients. Fig. 1 shows a flowchart of the proposed methodology.

A. DATA DESCRIPTION

The CXR images of pneumonia were collected from Guangzhou Women and Children's Medical Centre, Guangzhou [20] which is also publicly available in Kaggle [21]. The database consists of 5857 CXR images with the resolution varying from 400 pixels to 2000 pixels. The images from the database are separated into three categories: normal, bacterial pneumonia, and viral pneumonia. The samples from each class are shown in Fig. 2.

The number of images from normal, bacterial pneumonia, and viral pneumonia patients are 1583, 2779, and 1495 respectively, which are shown in Table 1.

Here two types of classifications have been performed where one is for multiclass classification, and the other is for binary class classification. For the binary classification, bacterial and viral pneumonia have been combined into a pneumonia class. Then the number of images for normal and pneumonia patients becomes 1583 and 4274, respectively. This implies that the normal class had been used to represent

TABLE 2. Dataset splitting into training and testing set for both multiclass and binary classification.

	Types	Training Set	Testing Set
Multiclass	Normal	1421	162
	Bacterial Pneumonia	2496	283
	Viral Pneumonia	1343	152
Binary	Normal	1425	158
	Pneumonia	3846	428

27% of the images, while the pneumonia had been seen in 73% of the images. The datasets have been divided into training and testing sets. For multiclass classification, the whole dataset has been divided into a ratio of 89.81: 10.19 and for binary class classification, the whole dataset has been divided into a ratio of 90: 10 for training and testing the model. The data splitting is shown in Table 2.

B. PRE-PROCESSING

Preprocessing of the image data is critical because the quality of image preprocessing affects the classification results.

1) IMAGE CONTRAST ENHANCEMENT

In this study, the image contrast has been enhanced by Histogram Equalization (HE) to improve the model accuracy. Contrast is determined by diversity in color or brightness with one object to other objects in a similar viewpoint. It makes one object recognizable from other objects. It is mainly used for images which are related to scientific works such as X-Ray, Satellite, and Thermal images [22]. As the CXR images have been used here, it is also useful to apply image contrast enhancement for this study.

An HE technique named Contrast Limited Adaptive Histogram Equalization (CLAHE) is used for this study. It is a version of Adaptive Histogram Equalization (AHE). The HE method is applied for the entire image. In contrast, for AHE, an entire image is divided into small portions of rectangular-sized named tiles of an image, and AHE is applied for all the tiles individually [23]. It enhances the local contrast and edges. However, the AHE overamplifies the noise in the region where the image is nearly uniform [24]. CLAHE solves this problem by limiting the amplification. It clips the amplification by the clipping factor.

Though the normal CXR images are grayscale, the CXR images used in this study are obtained from the Kaggle pneumonia image dataset, defined by 3 channels. CLAHE can be used for both gray and color images [25]. In this study, the contrast has been enhanced by CLAHE while considering 'L', 'A', 'B' information [26], and the input data with three channels are required. For that reason, the input data is described as 3 channels instead of 1. For this study, a clipping factor of 2 and a tile size of 8×8 have been employed.

2) RESIZING

The database contains images in various sizes, and they are converted to a specific size so that it is easy to fit these into the CNN model. As a result, after performing CLAHE on the images the images are adjusted to the image for the model to 224×224 pixels in size.

3) NORMALIZATION

A large number of intensity values are used to depict an image. Hence, normalization is carried out to avoid any complexity without a large number of image pixels. The scale is adjusted from $0-255$ to $0-1$ to lessen the complexity of the images by dividing image pixel values by 255.

C. HYBRID CNN-PCA BASED FEATURE EXTRACTION

Availability of a large number of data, i.e., high dimensional data, creates problems in developing an effective predictive model. Again, the time-cost for training the predictive model is high. Sometimes some features do not change much with populations, i.e., hence holding less amount of information. As all the features of a dataset do not have an equal amount of information, it is required to reduce the dimension of data to reduce the model time complexity and error arising from the irrelevant features.

It can be performed using either feature selection (FS) or feature extraction (FE). The process of choosing a feature subset among the original features is called the FS technique. It is used when the use of original features and explainability of the model is maintained. Some algorithms have built-in FS techniques such as Regularized Regression and Random Forest. On the other hand, the FE method derives new feature space from the existing features while holding the most relevant data. It is used when the use of original features and explainability of the model is not required. Some algorithms, such as Deep Learning, have built-in FE techniques. PCA, linear discriminant analysis (LDA), etc., can be used as a separate tasks.

In this study, two FE techniques have been combined. Initially, the CNN model has been used to reduce the total 224×224 features to 512. Then PCA has been implemented to reduce the 512 features into 100.

1) FEATURE EXTRACTION USING CNN FROM RAW DATA

The most crucial aspect of the classification problem is feature extraction because the performance of a model is determined by how well the important features from the CXR images are extracted. It is necessary to extract the good features that have discriminated between the two classes to improve the classification performance of the model. Feature extraction is a technique that converts higher dimensional data into lower-dimensional, non-redundant, and informative data [27]. It enables further data processing and improved data management. Hence, a novel deep CNN has been built for extracting 512 important features for pneumonia detection using the CXR images since the features for these images are more complicated.

Fig. 3 demonstrates the proposed CNN model. A total of six convolutional layers form the proposed CNN model, whereas, after two consecutive convolutional layers, batch

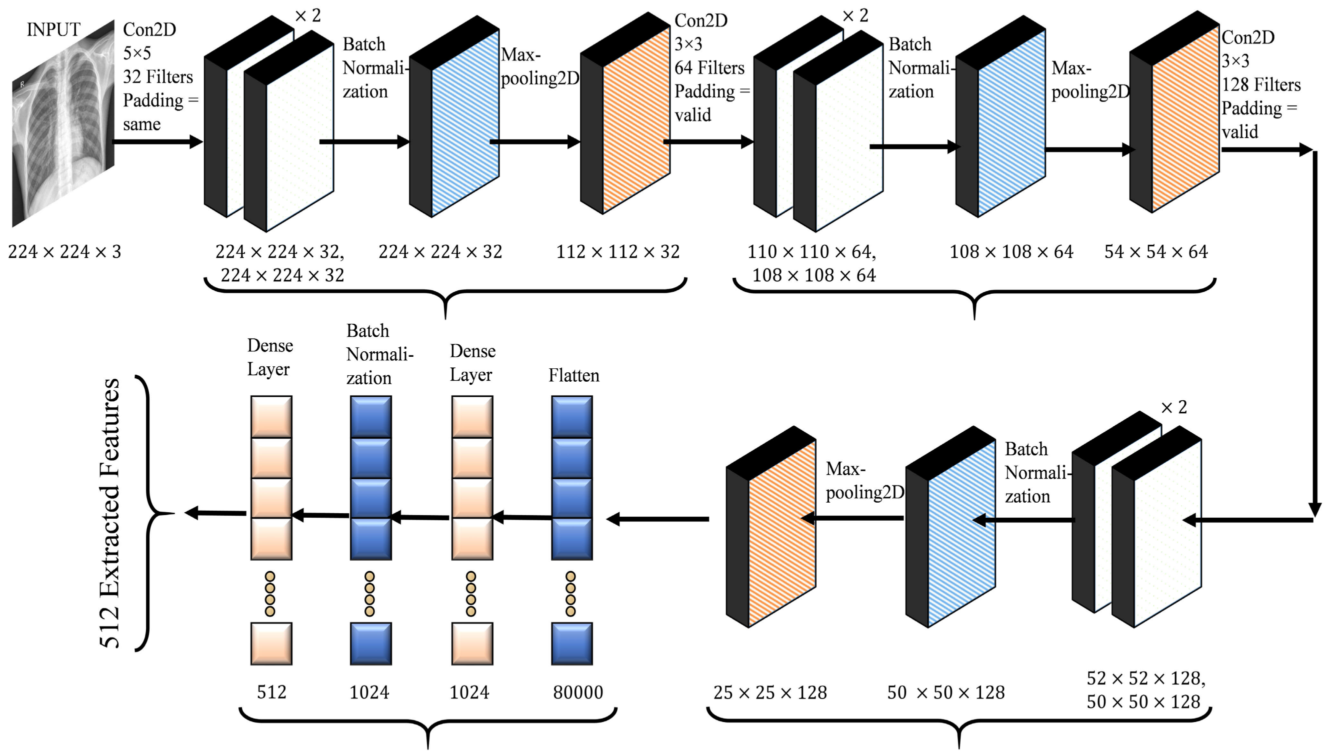

FIGURE 3. Proposed CNN model for features extraction.

normalization and a max-pooling layer are used. Batch normalization has been used because it makes the model faster to run and more stable by re-centering and re-scaling the inputs of the layers [28]. A pooling layer between two successive convolutional layers has been placed. Max-pooling with 2 × 2 filters has been utilized, which select the largest value from each cluster's whole neuron at the convolutional layers and can extract the most crucial components from the images [4], [29], [30]. A pooling layer between two successive convolutional layers has been placed. Max-pooling with 2 × 2 filters has been utilized to select the largest value from each cluster's whole neuron at the convolutional layers and extract the most crucial components from the images. The 'SAME' padding has been introduced in the first two convolutions layers since the output has been calculated by applying the filters to all image tuples. As a result, the border elements have been checked because they can often include crucial features. The border elements were computed with zero paddings. The 'VALID' padding, on the other hand, ignored the border elements. ReLU has been employed as an activation function to avoid the problem of disappearing the gradient [4]. Two dropout layers with a probability of 0.5 have been utilized where one dropout is used after the final max-pooling layer, and another is used after the first fully connected layer. Here the dropout layers are used for reducing overfitting by frequently avoiding training all nodes in each layer during the training phase, resulting in a significant boost in the training speed [31]. The Adam optimizer has been chosen because it is highly accurate for the CNNs, and performs better when training on large amounts of data [32]. As the CXR images dataset used in this study is labeled, the loss has been calculated using sparse categorical cross-entropy with the provided label in the dataset. The autoencoder, generally used for unlabeled data, has not been considered in this study [33]. The learning rate of the proposed model is 0.001, and trained the model for 100 epochs with a batch size of 32. Finally, the last dense layer has been used to extract the 512 discriminant features from each image. Table 3 shows the summary of the deep CNN model.

2) FEATURE EXTRACTION USING PCA

PCA is an unsupervised statistical technique of dimensionality reduction. It transforms the possibly correlated features into linearly uncorrelated features [34]–[36]. It can be described using the following steps:

1) Perform data standardization which means the values of each feature in the data are given a zero-mean and unit-variance through feature standardization [37]. It has a significant effect on PCA. As scaling can affect the covariance matrix. To determine the correlation between two features, an element-wise multiplication between them is performed. Hence, if both features are not scaled with the same range, the purpose of the covariance matrix will be diverse. After extracting 512 features using the CNN, standardization, i.e., feature scaling, has been performed on the data. It has been

TABLE 3. Summary of proposed CNN for feature extraction.

Layer (type)	Output Shape	Param
conv2d_input (InputLayer)	[(None, 224, 224, 3)]	0
conv2d (Conv2D)	(None, 224, 224, 32)	2432
conv2d_1 (Conv2D)	(None, 224, 224, 32)	25632
batch_normalization(BatchNo	(None, 224, 224, 32)	128
activation (Activation)	(None, 224, 224, 32)	0
max_pooling2d (MaxPooling2D)	(None, 112, 112, 32)	0
conv2d_2 (Conv2D)	(None, 110, 110, 64)	18496
conv2d_3 (Conv2D)	(None, 108, 108, 64)	36928
batch_normalization_1 (Batch	(None, 108, 108, 64)	256
activation_1 (Activation)	(None, 108, 108, 64)	0
max_pooling2d_1 (MaxPooling2	(None, 54, 54, 64)	0
conv2d_4 (Conv2D)	(None, 52, 52, 128)	73856
conv2d_5 (Conv2D)	(None, 50, 50, 128)	147584
batch_normalization_2 (Batch	(None, 50, 50, 128)	512
activation_2 (Activation)	(None, 50, 50, 128)	0
max_pooling2d_2 (MaxPooling2	(None, 25, 25, 128)	0
dropout (Dropout)	(None, 25, 25, 128)	0
flatten (Flatten)	(None, 80000)	0
dense (Dense)	(None, 1024)	81921024
batch_normalization_3 (Batch	(None, 1024)	4096
activation_3 (Activation)	(None, 1024)	0
dropout_1 (Dropout)	(None, 1024)	0
feature_dense112 (Dense)	(None, 512)	524800

performed by this using equation 1 [38].

$$x' = \frac{x - \bar{x}}{\sigma} \tag{1}$$

where,

x = Original feature vector

$\bar{x}$ = Mean of that feature vector

σ = The standard deviation

Let, Z be the standardized version of feature matrix X.

2) The covariance matrix for this study has been determined using the matrix $A = Z \cdot Z^T$.
3) After calculating the covariance matrix, the eigenvector and the eigenvalue have been calculated. Calculate eigenvalues using $(A - \lambda I) = 0$ and eigenvector by solving $(A - \lambda I)V = 0$ for different values of lambda. For this study, there are 512 eigenvalues, and each eigenvector consists of 512 elements.
4) Then sort the eigenvalues in descending order and the respective eigenvector, and among the 512 eigenvalues, top 100 eigenvalues are selected, and the dimension of the eigenvector matrix, E is (512×100).
5) Multiply the feature matrix, X with the eigenvector matrix, E. The dimension of the new feature space is $(5856 \times 512) \cdot (512 \times 100) = (5856 \times 100)$. Hence, the dimension is reduced.

D. EXTREME LEARNING MACHINE

ELM has been proposed by Huang *et al.* [39] to minimize the training time costing due to the iterative model parameter tuning process. In this study, for the binary class classification, 100 features have been fed into the input nodes, and there are 500 nodes in the hidden layer and one output node. For the multi-class classification, there are a total of 3 output nodes in the ELM, which is shown in Fig. 4. As a simple single hidden layer ELM has been used, there is no error back-propagation process. Output weight matrix has been calculated using the pseudo-inverse technique.

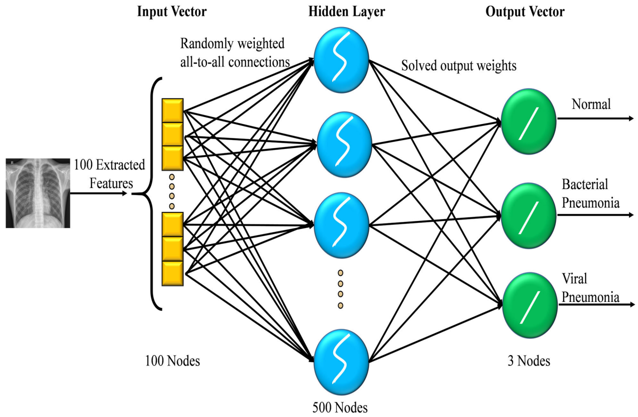

FIGURE 4. Proposed ELM for classification.

Let's, consider a training sample $\{X_1, Y_1\} = \{x_{(1,m)}, y_{(1,t)} : m \epsilon R+, t \epsilon R+\}$. X be the input and Y be the output for this study. Then, all the train samples can be represented by a matrix format such as

$$X_{(n,m)} = \begin{bmatrix} x_{(1,1)} & x_{(1,2)} & \cdots & x_{(1,m)} \\ x_{(2,1)} & x_{(2,2)} & \cdots & x_{(1,m)} \\ x_{(3,1)} & x_{(3,2)} & \cdots & x_{(1,m)} \\ \vdots & \vdots & & \vdots \\ x_{(n,1)} & x_{(n,2)} & \cdots & x_{(n,m)} \end{bmatrix}$$

$$Y_{(n,t)} = \begin{bmatrix} y_{(1,1)} & y_{(1,2)} & \cdots & y_{(1,t)} \\ y_{(2,1)} & y_{(2,2)} & \cdots & y_{(1,t)} \\ y_{(3,1)} & y_{(3,2)} & \cdots & y_{(1,t)} \\ \vdots & \vdots & & \vdots \\ y_{(n,1)} & y_{(n,2)} & \cdots & y_{(n,t)} \end{bmatrix}$$

where, n be the number of instances, m be the number of attributes and t be the number of output nodes. Hence, for this study $m = 100$ as the feature space has been reduced to 100 and value of n will be changed with the size of train and test dataset. For binary class $t = 1$ and for multiclass classification $t = 3$. Then, this randomly generates the input weight $W_{(m,N)}$ and bias $B_{(1,N)}$ matrix. Where, N = number of hidden nodes.

$$W(m, N) = \begin{bmatrix} w_{(1,1)} & w_{(1,2)} & \cdots & w_{(1,N)} \\ w_{(2,1)} & w_{(2,2)} & \cdots & w_{(1,N)} \\ w_{(3,1)} & w_{(3,2)} & \cdots & w_{(1,N)} \\ \vdots & \vdots & & \vdots \\ w_{(m,1)} & w_{(m,2)} & \cdots & w_{(m,N)} \end{bmatrix}$$

$$B(1, N) = \begin{bmatrix} b_{(1,1)} & b_{(1,2)} & \cdots & b_{(1,N)} \end{bmatrix}$$

where, m be the number of attributes and N be the number of hidden nodes. For this study, the value of N will be 500.

Then, the output of the hidden layer is calculated using

$$H_{(n,N)} = G(X_{(n,m)} \cdot W_{(m,N)} + B_{(1,N)}).$$

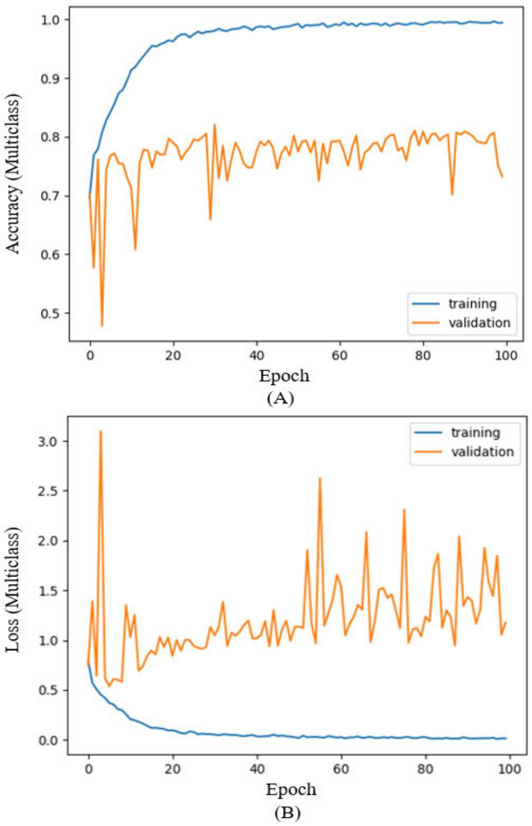

FIGURE 5. (A) Accuracy, (B) Loss of training and validation sets for multiclass.

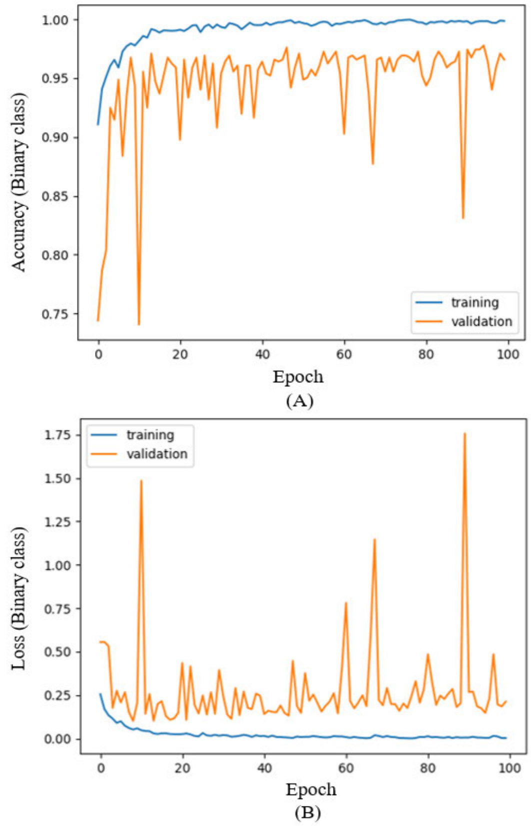

FIGURE 6. (A) Accuracy, (B) Loss of training and validation sets for binary classification.

where, $G(x)$ be the activation function. In this study ReLu activation function has been used.

$$H(n,N) = \begin{bmatrix} h_{(1,1)} & h_{(1,2)} & \cdots & h_{(1,N)} \\ h_{(2,1)} & h_{(2,2)} & \cdots & h_{(1,N)} \\ h_{(3,1)} & h_{(3,2)} & \cdots & h_{(1,N)} \\ \vdots & \vdots & & \vdots \\ h_{(n,1)} & h_{(n,2)} & \cdots & h_{(n,N)} \end{bmatrix}$$

Finally, the output layer weight $\beta_{(N,t)}$ is calculated by using the Moore-Penrose pseudo inverse.

$$\beta_{(N,t)} = H^{\dagger}_{(N,n)} \cdot T_{(n,t)}$$

$T =$ Output of training data
$t =$ number of outputs

The proposed ELM for this study can be expressed using the following steps:

Algorithm Extreme Learning Machine

1) Randomly generates the input weight $W_{(m,N)}$ and bias $B_{(1,N)}$ matrix.
2) Determine the output $H_{(n,N)}$ of the hidden layer.
$$H_{(n,N)} = G(X_{(n,m)} \cdot W_{(m,N)} + B_{(1,N)})$$
3) Determine the output weight matrix $\beta_{(N,t)}$
$$\beta_{(N,t)} = H^{\dagger}_{(N,n)} \cdot T_{(n,t)}$$
4) Make prediction using $\beta_{(N,t)}$

IV. RESULTS & ANALYSIS

A. QUANTITATIVE ANALYSIS

A confusion matrix is a tabular representation in an easily understandable format used to analyze the performance of a classifier. Table 4 represents the confusion matrix.

Where true positive, true negative, false positive, and false negative represented as TP, TN, FP, and FN respectively. For evaluating the classification performance of the different approaches, several evaluation criteria have been considered which are accuracy, precision, recall, sensitivity, specificity, f1-score, and receiver operating characteristics (ROC) curve [40]–[43].

TABLE 4. Confusion matrix.

	Detected as Normal	Detected as Pneumonia
Actually Normal	TP	FN
Actually Pneumonia	FP	TN

B. RESULT ANALYSIS

The experiments and outcomes of various performance measurements are mentioned in this section. Keras had been used

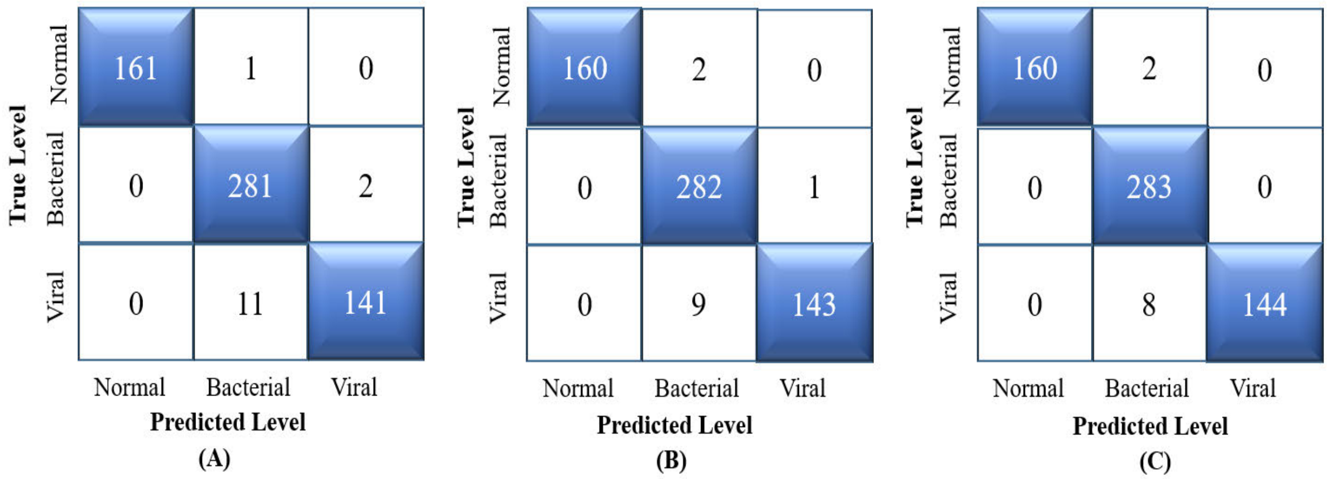

FIGURE 7. Confusion matrix for multiclass classification: (A) without CLAHE & PCA, (B) with only PCA, (C) using both CLAHE & PCA.

to implement all of the machine and deep learning algorithms, with TensorFlow as the backend, which runs at the Pycharm Community Edition19 (2020.2.3 × 64) software. For the training and testing of the model, a PC with an Intel(R) Core(TM) i7-6700 CPU @3.40GHz processor, 32GB RAM, and an NVIDIA GeForce GTX 1650 SUPER 4 GB GPU running on a 64-bit Windows 10 Pro operating system has been used.

First, the CXR images have been preprocessed. After that, a novel CNN model for dimensionality reduction has been proposed. Fig. 5 showed the training and validation accuracy for the multiclass classification, which are 98.28% and 82.98% respectively, whereas the training and validation losses are 0.015 and 0.52 respectively during the dimensionality reduction process.

Fig. 6 demonstrates the training and validation accuracy, losses during the features extraction process for the binary class classification. The training and validation accuracy are 99.98% and 99.78%, respectively, whereas the training and validation losses are 0.0027, and 0.10 respectively.

1) RESULTS FOR MULTICLASS CLASSIFICATION

The extreme learning algorithm has been trained using 5260 data of both normal, bacterial, and viral pneumonia-infected persons where 1421 images were from normal, 2496 images from bacterial pneumonia, and 1425 images from viral pneumonia patients. To determine the performance of the model, 597 data have been tested by the ELM model where the number of images for normal, bacterial, and viral pneumonia patients are 162, 283, and 152, respectively. First, all 512 features have been used to train the model. Second, PCA has been implemented for selecting 100 discriminant features to check whether the performance of the model is increasing or not. Finally, CLAHE has been used to preprocess the images, and then PCA has been used that achieved the best result in every benchmark. To evaluate the stability of the ELM model, a confusion matrix has been employed to calculate the accuracy, precision, recall, f1-score, and area under the curve (AUC), which are shown in Fig. 7. In the medical sector, the recall should be maximized since the patient who has been infected with different types of pneumonia must be correctly identified as pneumonia.

TABLE 5. Results of multiclass classification using only CNN.

Type	Precision	Recall	F1-Score	Accuracy
Normal	0.93	0.94	0.93	-
Bacterial Pneumonia	0.80	0.88	0.84	-
Viral Pneumonia	0.73	0.59	0.65	-
Average	0.82	0.80	0.81	82.25%

TABLE 6. Results of multiclass classification using extreme learning machine (CNN-ELM) without using CLAHE & PCA.

Type	Precision	Recall	F1-Score	Accuracy
Normal	1.00	0.99	0.99	-
Bacterial Pneumonia	0.95	0.99	0.97	-
Viral Pneumonia	0.99	0.91	0.95	-
Average	0.98	0.96	0.97	97.09%

For detecting the pneumonia, the CNN provides an average precision, recall and accuracy of 0.82, 0.80, and 82.25%, respectively which are shown in Table 5. It was observed that the classification performance using the CNN only was not quite good specially for the multiclass classification. For that reason, different combinations have been explored for the classification of the multivariate pneumonia.

Table 6 showed the result for classification of pneumonia using ELM-CNN without CLAHE & PCA. That means that after extracting features using CNN, these three classes have been classified with the help of ELM. The model has achieved an accuracy and recall of 97.09% and 96%.

Then, the model's performance has been enhanced by applying PCA to select 100 features from the 512 features,

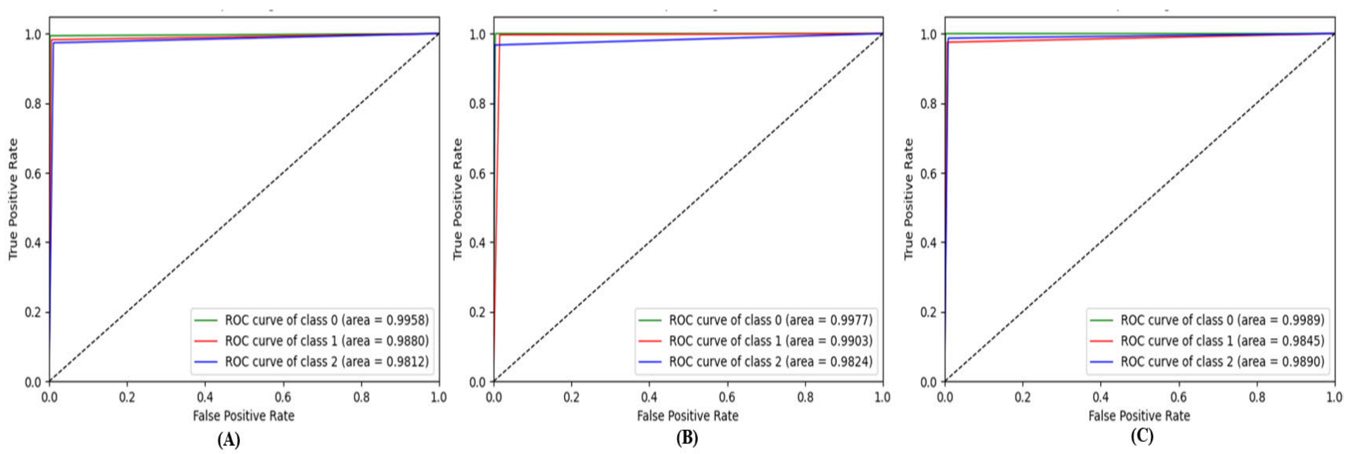

FIGURE 8. ROC curve for multiclass classification: (A) without CLAHE & PCA, (B) with only PCA, (C) using both CLAHE & PCA.

TABLE 7. Results of multiclass classification for extreme learning machine using only hybrid CNN-PCA as features extractor (CNN-PCA-ELM).

Type	Precision	Recall	F1-Score	Accuracy
Normal	1.00	0.99	0.99	-
Bacterial Pneumonia	0.96	1.00	0.98	-
Viral Pneumonia	0.99	0.94	0.97	-
Average	0.99	0.97	0.98	97.98%

TABLE 8. Results of multiclass classification for ELM using both CLAHE & hybrid CNN-PCA as features extractor (CLAHE-CNN-PCA-ELM).

Type	Precision	Recall	F1-Score	Accuracy
Normal	1.00	0.99	0.99	-
Bacterial Pneumonia	0.97	1.00	0.98	-
Viral Pneumonia	1.00	0.95	0.97	-
Average	0.99	0.98	0.98	98.32%

TABLE 9. Processing time for multiclass classification.

Model	Training Time (sec)	Testing Time (sec)
CNN	4076.068	1.377
CNN-ELM	4094.247	0.029
CNN-PCA-ELM	4090.911	0.00093
CLAHE-CNN-PCA-ELM	4092.045	0.00099

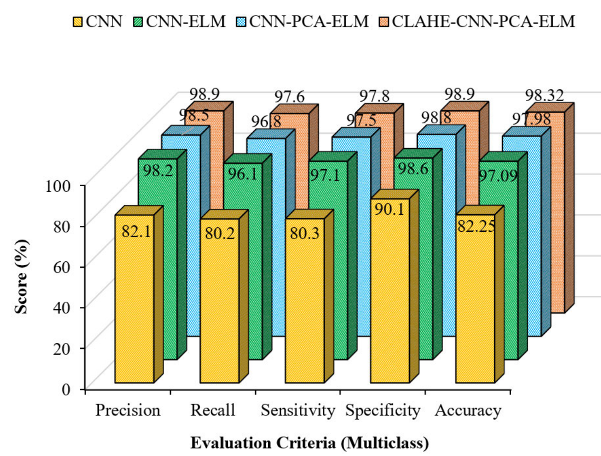

FIGURE 9. Graphical comparison for multiclass classification with different approaches.

which are extracted using CNN. Then ELM has been used to classify pneumonia from these 100 features and achieved accuracy and recall of 97.98% and 97%.

Table 7 showed the performance of the ELM using PCA for multiclass.

Furthermore, the performance has been improved by using CLAHE, which means enhanced the contrast of the images, extracted the feature using hybrid CNN-PCA, and classified the disease using ELM. Table 8 showed that the result with accuracy and recall of 98.32% and 98%. The AUC of the ELM model for the multiclass classification using only ELM, ELM with PCA, and ELM with both CLAHE & Hybrid CNN-PCA are showed in Fig. 8. It is used as an evaluation measure to fine-tune the performance of a machine learning model [44]. From Table 9, it is concluded that the training time utilizing the ELM with hybrid CNN-PCA is just 15.977 seconds longer than the training time using the CNN only. Following the extraction of the features, the testing time for the ELM using hybrid CNN-PCA is just 0.00099 seconds, which is significantly less than the testing time of 1.377 seconds using the conventional CNN. It is negotiable if the classification performance of the ELM with hybrid CNN-PCA has been compared to the classification performance of the CNN-based system. As a result, it can be argued that the overall performance of ELM has been significantly superior to the performance of the CNN alone. From Fig. 9, it was observed that the accuracy and specificity of ELM with both CLAHE and CNN-PCA was found to be 98.32% and 98.9%, respectively, which were higher than that by ELM without PCA (97.09% and 98.6%), ELM with only PCA (97.98% and 98.8%) and CNN only (82.25% and 90.10%).

The image contrast has been improved by applying CLAHE that makes the images more classifiable. The hybrid

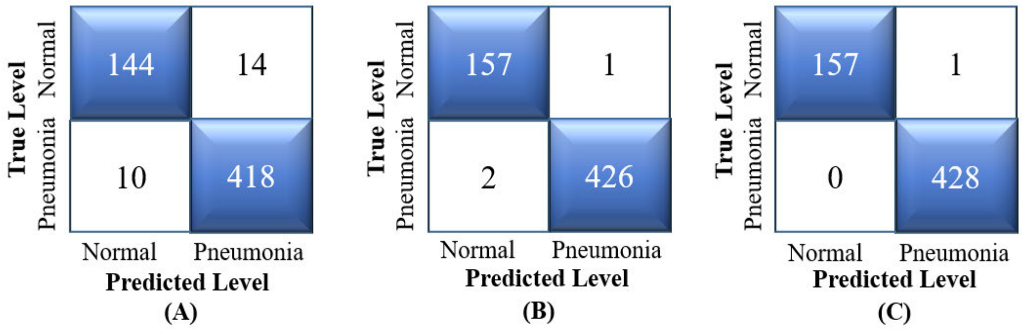

FIGURE 10. Confusion matrix for binary class classification: (A) without CLAHE & PCA, (B) with only PCA, (C) using both CLAHE & PCA.

TABLE 10. Results of binary classification using CNN.

Type	Precision	Recall	F1-Score	Accuracy
Normal	0.91	0.88	0.90	-
Pneumonia	0.96	0.97	0.96	-
Average	0.94	0.92	0.93	94.53%

TABLE 11. Results of binary classification for extreme learning machine without using CLAHE & PCA (ELM-CNN).

Type	Precision	Recall	F1-Score	Accuracy
Normal	0.94	0.91	0.92	-
Pneumonia	0.97	0.97	0.97	-
Average	0.95	0.94	0.95	95.90%

PCA-CNN feature extraction technique reduces the number of features, removing irrelevant and redundant features and minimizing the model parameter. Due to these reasons, the ELM model with CLAHE & PCA has produced better results than the other three models for multiclass classification.

2) RESULT FOR BINARY CLASSIFICATION

For binary class classification, 5271 data has been used for both the normal and pneumonia-infected images to train the model, where 1425 images were from the normal patients and 3846 images from the pneumonia patients. To determine the model's performance, 586 data was used to test the ELM model, where 158 images were from normal and 428 images from the pneumonia patients. Here the same approaches have been used as the multivariant classification. Fig. 10 show the confusion matrix for the binary classification. The precision, recall, f1-score have been calculated from the confusion matrix.

Table 10 shows the result for binary classification using only CNN. The average precision, recall, and accuracy is 0.94, 0.92, and 94.53%, respectively. The average precision, recall, and f1-score for ELM-CNN without PCA are 0.95, 0.94, and 0.95, respectively which are shown in Table 11.

The model has been achieved a precision, recall, and f1-score of 0.99, 0.99, and 0.99, respectively, using ELM with Hybrid CNN-PCA (Table 12). In the final experiment,

TABLE 12. Results of binary classification for extreme learning machine using only hybrid CNN-PCA as features extractor (CNN-PCA-ELM).

Type	Precision	Recall	F1-Score	Accuracy
Normal	0.99	0.99	0.99	-
Pneumonia	1.00	1.00	1.00	-
Average	0.99	0.99	0.99	99.48%

TABLE 13. Results of binary classification for ELM using both CLAHE & Hybrid CNN-PCA as features extractor (CLAHE-CNN-PCA-ELM).

Type	Precision	Recall	F1-Score	Accuracy
Normal	1.00	0.99	1.00	-
Pneumonia	1.00	1.00	1.00	-
Average	1.00	1.00	1.00	99.83%

TABLE 14. Processing time for binary classification.

Model	Training Time (sec)	Testing Time (sec)
CNN	4065.614	1.340
CNN-ELM	4088.866	0.0089
CNN-PCA-ELM	4083.859	0.00398
CLAHE-CNN-PCA-ELM	4085.246	0.00498

CLAHE and Hybrid CNN-PCA both have been used. The proposed model has achieved a precision, recall, and f1-score of 1.00, 1.00, and 1.00 respectively. It has shown a promising result compared to the existing methods. The ROC curve of the ELM model is shown in Fig. 11.

From Table 14, it is observed that the training time using the ELM with hybrid CNN-PCA is only 19.632 seconds longer than that by the CNN only. After extracting the features, the testing time for the ELM with hybrid CNN-PCA is only 0.00498, which is much smaller than the testing time of 1.340 using the CNN only. It is negotiable if the classification performance of the ELM with hybrid CNN-PCA has been considered against the performance using CNN. Therefore, it is concluded that the overall performance of the ELM for the binary classification of pneumonia is relatively better than the performance of the CNN alone.

From Fig. 12, it was observed that the accuracy and specificity of ELM with both CLAHE and CNN-PCA was found to be 99.83% and 100%, which were higher than the accuracy

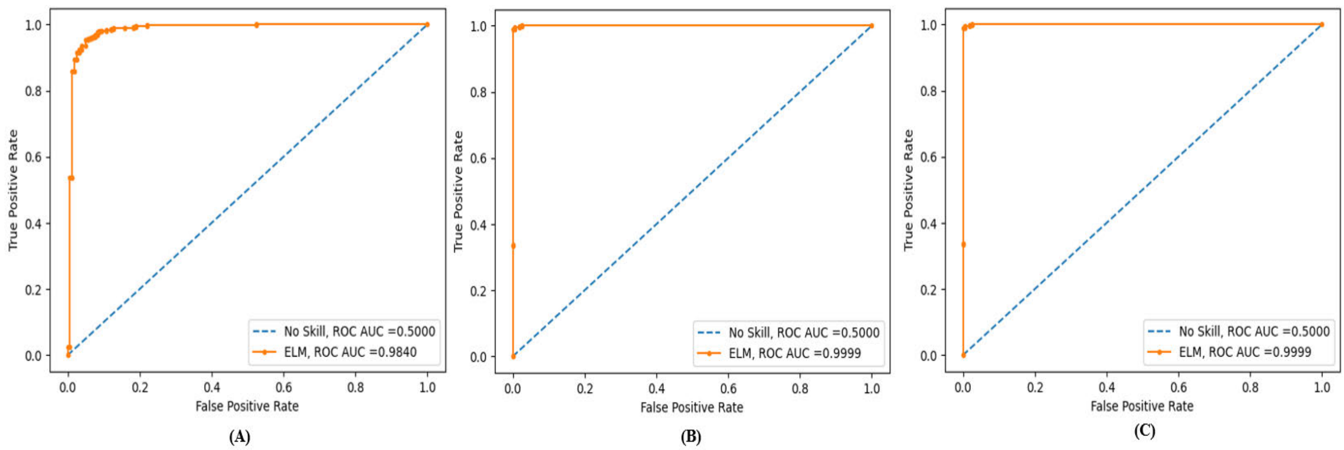

FIGURE 11. ROC curve for binary classification: (A) without CLAHE & PCA, (B) with only PCA, (C) using both CLAHE & PCA.

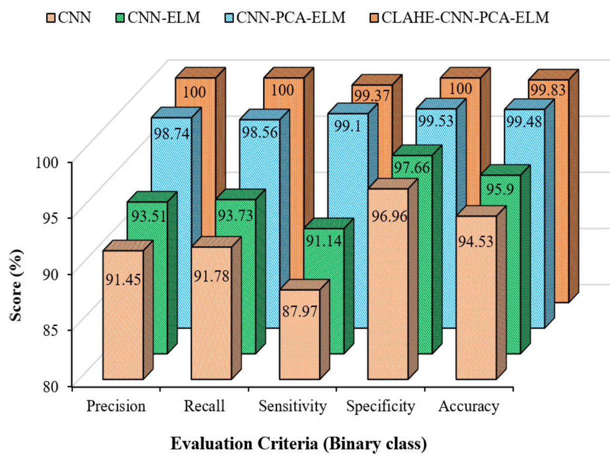

FIGURE 12. Graphical comparison for binary class classification with different approaches.

of ELM without PCA (95.90% and 97.66%), ELM with only PCA (99.48% and 99.53%) and CNN only (94.53% and 96.96%). Due to the similar reasons for the multiclass classification, the ELM with CLAHE & CNN-PCA performed better than the other three approaches for the binary class classification. In the multiclass classification, the pneumonia patients were additionally divided into viral and bacterial pneumonia. As the number of classes increased, the model performance decreased.

C. PERFORMANCE COMPARISON ANALYSIS

From the results, it was clear that the accuracy of the binary classification was higher than that of the multiclass classification. It should be acknowledged that it is more challenging to increase the accuracy as well as other performance criteria for the multiclass classification, particularly after reaching a certain degree of accuracy. In the case of the multiclass classification, the accuracy was raised by 0.89% when compared between the ELM without CLAHE & PCA (Table 6) and ELM with hybrid CNN-PCA (Table 7). Again, a further increase in accuracy of 1.23% was observed when compared between the ELM without CLAHE & PCA (Table 6) and ELM with both CLAHE & hybrid CNN-PCA (Table 8). It is expected that this incremental accuracy would help in the detection of these types of diseases. Furthermore, the accuracy of the three-class classification using only CNN was 82.25% (Table 5), while after using ELM, this classification accuracy was boosted up to 98.32% (Table 8), which is almost 16% higher than that obtained by the CNN only. For three multiclass classification using ELM, better classification performance was also obtained than the state-of-the-art models, which are shown in the latter section.

In this section, the approaches used in this study have also been checked for statistical significance. In the CNN-ELM approach, CNN is used for the feature extraction and ELM for the classification. On the other hand, in the CNN-PCA-ELM approach, the hybrid CNN-PCA is used for the feature extraction and ELM for the classification. Here, these two main approaches have been checked for both the binary and multiclass classifications. By using an inferential statistic known as t-test (t-statistics), researchers can evaluate whether the outcome of the two models differ significantly [45]. In this study, a t-test has been performed and which gave a p-value. Here, p-values have been calculated for the CNN-PCA-ELM and CNN-ELM approaches for both the binary and multiclass classifications to identify which model is statistically significant [46], [47]. A p-value of 0.031 ($P<0.05$) for both the binary and multiclass classifications have been obtained when compared between the CNN-PCA-ELM and CNN-ELM approaches, indicating that CNN-PCA-ELM is statistically significant for both types of classification.

D. PERFORMANCE COMPARISON WITH PREVIOUS WORKS

In this section, it has been demonstrated that how the extreme learning machine method performs better with PCA than the

TABLE 15. Performance comparison of ELM model for classification with existing models.

Name	Precision	Recall	Accuracy	AUC
Rahman et al. [6]	93.7%	93.2%	93.3%	95.00%
Proposed Model	**99%**	**98%**	**98.32%**	**99.01%**
Rahman et al. [6]	97%	99%	98.00%	98.00%
Proposed Model	**99.12%**	**100%**	**99.76%**	**100%**
Liang et al. [14]	89.10%	96.7%	90.5%	95.3%
Jain et al. [4]	—	98%	92.31%	—
Ayan et al. [11]	87%	88%	87%	—
Chouhan et al. [5]	93.28%	99.62%	96.39%	99.34%
Proposed Model	**98.26%**	**100%%**	**99.52%**	**100%**
Almaslukh [48]	98.9%	98.9%	98.9%	—
Proposed Model	**99.61%**	**99.80%**	**99.57%**	**99.99%**
Mittal et al. [8]	96.77%	98.28%	96.36%	—
Proposed Model	**99.53%**	**100%**	**99.65%**	**99.99%**
Wu et al. [7]	90%	95%	96.9%	—
Proposed Model	**99.36%**	**99.93%**	**99.48%**	**99.99%**

earlier research in this sector. In section II, the proposed method has already gone over the specifics of the previous works. Rahman used four different pre-trained deep CNN transfer learning models [6]. They considered both multiclass and binary class classifications. For the multiclass classification, they used 597 data for testing their model and achieved an accuracy of 93.3%. The same data has been used for testing the ELM with CLAHE & PCA and achieved a higher result with an accuracy of 98.32% which are shown in Table 15. For the binary class classification, they have used 419 data for testing their different CNN models. They improved the model accuracy using DenseNet with an accuracy, sensitivity, and precision of 0.98, 0.99, and 0.97, respectively. The same data has been used for testing from the Kaggle CXR dataset and achieved higher accuracy, recall, and precision of 99.52%, 99.12%, and 99.12%, respectively. CNN was utilized by Liang *et al.* to identify the pneumonia patient. They used the same dataset to train and test their model using 624 test data [14]. Finally, they achieved an accuracy of 90.5%, a recall of 96.7%, and an AUC of 95.3%. Jain *et al.* used the same dataset for training and testing their various models using 624 images [4]. Their models achieved the best recall and accuracy, of 98% and 92.32%, respectively. Using VGG16 over the Xception network, Ayan *et al.* achieved the best accuracy [11]. They tested their model using 624 CXR images and achieved an accuracy and recall of 90.5%, and 96.7% respectively. Chouhan *et al.* utilized the same dataset for training their ensemble model, and they obtained 96.39% of accuracy, 99.62% of recall, and 99.34% of AUC [5].

The same data has been used for training and testing the model. The proposed model has achieved higher performance than their work with an accuracy, precision, and AUC of 99.04%, 97.66%, and 99.96%, respectively. Almaslukh proposed a lightweight DL method using pre-trained DensenNet121 for the detection of pneumonia [48]. They have used 700 test data from the Kaggle CXR dataset for testing their model. They have achieved an accuracy, precision, and recall of 98.9%, 98.9%, and 98.9%, respectively. The same data has been used for testing the ELM model with PCA and achieved higher performance with an accuracy, precision, and recall of 99.71%, 99.47%, and 99.47%, respectively. Mittal *et al.* trained their proposed model using CXR images from the Mendeley [8]. They tested their model using 878 images and achieved a high accuracy of 96.36%. The same data has been used for training and testing the model and achieved an accuracy of 99.20% which is higher than their model. Wu *et al.* proposed an ACNN-RF model to detect pneumonia. They tested their model using 1928 images and achieved an accuracy, precision, and recall of 96.9%, 90%, and 95% respectively [7]. The same data has been used for testing our ELM model with PCA and achieved higher performance with accuracy, precision, and recall of 99.22%, 98.10%, and 99.04%, respectively. From Table 15, it has been found that the proposed model outperformed eight state-of-the-art models.

From the above comparison, it can be stated that the proposed method is a robust and effective method for pneumonia classification. It has achieved the highest score in each benchmark for both the binary class and multiclass classifications. This study uses CLAHE to enhance the image contrast with a new hybrid CNN-PCA feature extraction technique. ELM has been used as the classifier that reduces the training time cost because it does not require any iterative tuning parameter. These newly designed features in the algorithm claim the novelty of the process. The data set used in the process is considerably imbalanced, which generally occurs for open-source data, and the model still achieved the highest accuracy. In this study, for the binary class classification, the ratio of pneumonia and normal is 2.69: 1, and for the multiclass classification, the ratio of normal, bacterial, and viral pneumonia is 1.06: 1.86: 1. Usually, a model with a balanced dataset performs better, so this is not discussed in this study. Another two important performance parameters of this type of image processing are Image quality and patients' age group. The dataset used in this study contains good quality CXR images of the children patients of one to five years old. The performances may vary with CXR images of the patients older than five years and with low-quality CXR images which may be the future scope of this research.

V. CONCLUSION

In the last few decades, pneumonia has been one of the significant causes of death for children and old-aged people worldwide. Patients with pneumonia who are diagnosed early have a higher chance of surviving. Recently detection of pneumonia using the CXR images has been performed by the researchers. If the detection rate is accurate, it can aid the medical practitioners in quickly diagnosing the disease and save the patient's life.

In this study, a novel ML model for automatic detection of various types of pneumonia with improved performance has been developed. In the first phase, the image quality has been enhanced using CLAHE. After applying CLAHE, the most prominent features have been extracted by developing a hybrid CNN-PCA feature extractor model. Finally, a novel ELM model has been proposed to detect various types of pneumonia from these extracted features. It has been found that the model ELM with CLAHE and hybrid CNN-PCA achieved high performance than any other model in this field. The accuracy, precision, and recall achieved for the binary class classification were 99.83%, 1.0, and 1.0, whereas the same performance parameters achieved for the multiclass classification were 98.32%, 0.99, and 0.98. For both multi-class and binary class classifications, the proposed CLAHE-ELM-CNN-PCA model performed admirably, which can assist medical practitioners in making an accurate and fast diagnosis of the pneumonia patients.

In future, the authors have planned to create a web app where this proposed method will be implemented. CXR images can be uploaded to the app, and pneumonia will be diagnosed automatically. It has also been planned to investigate how the proposed model will react with increased dataset size.

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MD. NAHIDUZZAMAN received the B.Sc. degree in computer science and engineering from the Rajshahi University of Engineering and Technology, Kazla, Rajshahi, Bangladesh, in 2018, where he is currently pursuing the M.Sc. degree. He is also working as a Lecturer with the Department of Electrical and Computer Engineering, Rajshahi University of Engineering and Technology. His research interests include machine learning, deep learning, and pattern recognition.

MD. OMAER FARUQ GONI received the B.Sc. degree in electrical and computer engineering from the Rajshahi University of Engineering and Technology, Kazla, Rajshahi, Bangladesh, in 2021. His research interests include deep learning, smart grid, and robotics.

MD. SHAMIM ANOWER (Member, IEEE) received the Ph.D. degree in electrical engineering from the University of New South Wales, Australia, in 2012. He is currently working as a Professor with the Department of Electrical and Electronic Engineering, Rajshahi University of Engineering and Technology. He has over 150 refereed publications, including journal (18 Q1 ranked in Scimago) and conference papers with H-index 20, i10-index 33, and 1205 citations. These cover the target sectors: "energy and mining technology," "quantum information, advanced digital, data science and ICT," and "cyber security." He is also a fellow of the Institute of Engineers Bangladesh (IEB).

MD. ROBIUL ISLAM received the B.Sc. degree in computer science and engineering from the Rajshahi University of Engineering and Technology, Kazla, Rajshahi, Bangladesh, in 2017, where he is currently pursuing the M.Sc. degree. He is currently working as a Lecturer with the Department of Electrical and Computer Engineering, Rajshahi University of Engineering and Technology. His research interests include segmentation, deep learning, and pattern recognition.

MOMINUL AHSAN received the B.Sc. degree from the Department of Computer Science and Engineering, State University of Bangladesh, Dhaka, Bangladesh, in 2008, the M.Eng. degree (Research) from the Faculty of Engineering and Computing, Dublin City University, Dublin, Ireland, in 2014, and the Ph.D. degree from the School of Computing and Mathematical Sciences, University of Greenwich, London, U.K., in 2019. He is currently working as an Associate Lecturer with the Department of Computer Science, University of York, U.K. Before joining at the University of York, he worked as a Postdoctoral Researcher with the Department of Engineering, Manchester Metropolitan University. His research interests include prognostics, data analytics, machine learning, reliability, power electronics, wireless communications, and wearable technology. He is a member of the Institution of Engineering and Technology (MIET), U.K., an Associate Fellow of the Higher Education Academy (AFHEA), U.K., and an Associate Member of the Bangladesh Computer Society. He was a recipient of the M.Eng. stipend at Dublin City University in 2010, the Ph.D. VC Scholarship at the University of Greenwich in 2014, and the Excellent Poster Award in the IEEE International Spring Seminar on Electronic Technology at Sofia, Bulgaria, in 2017.

JULFIKAR HAIDER is currently working as a Senior Lecturer in mechanical engineering with the Department of Engineering, Manchester Metropolitan University, U.K. He has been supervising research associates and Ph.D. students in the above areas. He has published and presented over 100 technical papers in international journals, conferences, and books. His main research interests include materials processing, thin film coating, composite materials, finite element analysis, and artificial intelligence; and it is in these areas that he is renowned for his work both nationally and internationally justified by his research outputs. He is acting as the Executive Editor of an international journal published by Taylor & Francis (*Advances in Materials and Processing Technologies*). He has received funding from Innovate, U.K., to conduct Eight Knowledge Transfer Partnership projects with industry worth more than a million.

SARAVANAKUMAR GURUSAMY (Member, IEEE) was born in Seithur, Tamil Nadu, India. He received the B.Eng. degree in electronics and instrumentation engineering from the National Engineering College, Kovilpatti, India, in 2004, the master's degree in control and instrumentation engineering from the Thiagarajar College of Engineering, Madurai, in 2007, and the Ph.D. degree from the Faculty of Instrumentation and Control Engineering, Kalasalingam Academy of Research and Education (KARE), India, in 2017. In 2009, he joined the Department of Instrumentation and Control Engineering, KARE, as a Lecturer. In 2011, he became an Assistant Professor. From 2014 to 2018, he worked as a Lecturer with the Department of Electrical and Computer Engineering, University of Gondar, Ethiopia. Then, he joined back to KARE, as a Senior Assistant Professor, where he served for a year. He is currently working as an Associate Professor with the Department of Electrical and Electronics Technology, Ethiopian Technical University, Addis Ababa, Ethiopia. His current research interests include virtual instrumentation, applications of evolutionary algorithms for control problem, nonlinear system identification, multivariable PID controller, model predictive control, autonomous vehicle, and mobile robotics.

RAKIBUL HASSAN received the B.Sc. degree in computer science and engineering from the Rajshahi University of Engineering and Technology, Rajshahi, Bangladesh, in 2018, where he is currently pursuing the M.Sc. degree. He is also working as a Lecturer with the Department of Electrical and Computer Engineering, Rajshahi University of Engineering and Technology. His research interests include machine learning, deep learning, and pattern recognition.

MD. RAKIBUL ISLAM received the B.Sc. degree in electrical and computer engineering from the Rajshahi University of Engineering and Technology, Kazla, Rajshahi, Bangladesh, in 2021. His research interests include deep learning and pattern recognition.