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DETECTION OF LUNG DISEASES FOR PNEUMONIA USING MACHINE AND DEEP LEARNING APPROACHES

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Abstract

Pneumonia disease is a dangerous one declared by WHO. It may be affected in one or both lungs generally affected by viruses or bacteria. Since the arrival of the novel Covid-19, several types of research have been initiated for its accurate prediction across the world. The earlier lung disease pneumonia is closely related to Covid-19, as several patients died due to high chest congestion (pneumonic condition). It is challenging to differentiate between Covid-19 and pneumonia lung diseases for medical experts. Chest X-ray imaging is the most reliable method for lung disease prediction. In this paper, we propose a novel framework for lung disease predictions differentiated by two categories "Pneumonia" and "Normal" from the chest X-ray images of patients using covnets, data acquisition, image quality enhancement, features extraction, and disease anticipation. Numerical illustrations were also provided to prove the results and discussions.

Keywords: Image Processing, Chest X-ray image, CNN, Data acquisition, and Covnets.

1. Introduction

The arrival of Covid-19 has brought significant threats to human life which started in China in November 2019 and later on spread across the world. It has been reported that more than 63.2 million people have already been infected in the world, which includes approximately 1.47 million deaths. The world health organization (WHO) continuously provides the necessary information for nations to protect against Covid-19 [1]. Countries like the United States, India, Brazil, Russia, France, Italy, and China are highly suffered nations from this threat [2]. Lung infections in chest X-ray images have been found in the form of consolidations, blunted costophrenic angles, broadly distributed nodules, cavitations, and infiltrates [3]. Therefore, radiologists detect several conditions like pneumonia, pleurisy, nodule, effusion, infiltration, fractures, pneumothorax, and pericarditis using X-ray images [4] and [5].

Detection and classification of lung diseases using chest X-ray images is a complex process for radiologists. Therefore, it received significant attention from researchers to develop automatic lung disease detection techniques [6], [7], and [8]. Since the past decade, many computers aided diagnosis (CAD) systems have been introduced for lung disease detection using X-ray images. But such systems failed to achieve the required performance for lung disease detection and classification. The recent Covid-19 assisted lung infections have made these tasks very challenging for such CAD systems. It is essential to detect the appearance of pneumonia in the lungs and its classification into Covid-19, bacterial, and viral infections.

The sets of feature vectors have been built from the ROI images using visual, texture, intensity, and invariant moment features. We have also proposed a robust feature normalization technique to enhance detection accuracy. After that, we applied several machine learning and soft computing techniques for classification which includes SVM, ANN, KNN, and ensemble classifiers. In addition to this, a deep learning approach using RNN with the LSTM model is designed to estimate the probabilities of lung conditions and early prediction to meet higher accuracy and minimum computational efforts. A deep experimental evaluation of the proposed model has been performed with state-of-the-art Covid-19 detection methods.

2. Related works

Recently, the accurate detection of lung diseases like Covid-19 and pneumonia has received significant attention. Computer vision and soft computing techniques have designed CAD systems for X-ray-based lung disease prediction. Recently researchers heavily relied on deep learning approaches due to their superiority in automatic feature extraction and high detection accuracy. In this section, we present a brief review of deep learning and computer vision techniques for pneumonia disease detection using chest X-ray images. Furthermore, we summarize the research motivation and highlight the major contributions of this work.

This classification provides appropriate medical attention to pneumonic patients. Several works have been presented with CAD systems for Covid-19, and automated image processing and deep learning techniques [9] have been developed for pneumonia disease detections using chest X-ray images. As deep learning is a fully automatic feature learning and extraction technique, it takes a longer time to complete dataset training and detection. Therefore, such solutions are not reliable and robust against the increased number of datasets. Deep learning techniques such as convolutional neural networks (CNN) gained attention for lung disease detection due to better accuracy and feature representation [10]. However, computational complexity is not yet discussed and addressed by any of the research. The computational complexity of CNN is higher due to the high-dimensional feature space for each X-ray image.

No vaccine for this threat has been developed in the first 6–8 months of Covid-19 as many countries were working on its production. Finally, a few countries have been able to develop a vaccine for Covid-19, which is still in the development or testing stage. The people infected with Covid-19 have moderate or mild symptoms such as fever, cough, and breathing shortness. However, people suffered from severe pneumonic conditions in their lungs that resulted in death as well [11], [12], [13], and [14]. Most of the people, who died from Covid-19, had suffered high chest congestion (pneumonia) due to a significant reduction in oxygen level which led to a major heart attack [15]. On the other hand, pneumonia is also a kind of lung disease that leads to inflammation in the small air sacs within the lungs of the human body.

Apart from this, lung cancer is another type of disease that has a significant threat to humans [16] and [17]. The WHO claims that approximately 8 million people have suffered from lung cancer to date. But this number is not higher than the lung diseases caused by Covid-19 and pneumonia within 15 months. Several studies have been presented on lung cancer for its early prediction using computer vision and soft computing methods [18], [19], and [20].

3. Chest X-ray image dataset

The chest X-ray image dataset depicts clear lungs images without any areas of abnormal indication and opacification in the image (Fig. 1a). Bacterial pneumonia indicated in the middle (Fig. 1b) typically exhibits a focal lobar consolidation, in this case in the right upper lobe (white arrows). The viral pneumonia shown on the right side (Fig. 1c) indicate the manifests with a more diffuse ‘‘interstitial’’ pattern in both lungs.

Fig. 1a Chest X-ray normal image

Fig. 1b Chest X-ray bacterial pneumonia image

Fig. 1c Chest X-ray viral pneumonia image

The benchmark open-source dataset includes three different folders namely training, testing and validation. The root folder contains another two subfolders namely pneumonia and normal. In this dataset contains 5863 X-ray images in the format of JPEG. Chest X-ray images (anterior posterior) under selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children’s Medical Center, Guangzhou. The dataset collection using Kaggle website (https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia)

4. Proposed Methodology

4.1 Convolution Neural Networks

A covnets is a sequence of layers, and every layer transforms one volume to another through a differentiable function. The layers cab divided into four types. (i) Input Layer: This layer holds the raw input of the image with width 32, height 32, and depth 3, (ii) Convolution Layer: This layer computes the output volume by computing the dot product between all filters and image patches. (iii) Activation Function Layer: This layer will apply an element-wise activation function to the output of the convolution layer. Some common activation functions are RELU: max(0, x), Sigmoid: 1/(1+e^-x), Tanh, Leaky RELU, etc. The volume remains unchanged hence output volume will have dimensions 32 x 32 x 12. (iv) Pool Layer: This layer is periodically inserted in the covnets and its main function is to reduce the size of volume which makes the computation fast reduces memory and also prevents overfitting.

4.2 Performance of Test Statistics

The term "sensitivity" (Table 1) tells us out of the total number of people who have the disease (e.g., COVID-19), the number that is correctly classified as having the disease by the model. The specificity of the model is its ability to determine healthy cases correctly. The positive predictive value (or precision) of the model means out of the total who are detected as disease positive (such as COVID-19 positive) by the model, how many of them are in fact disease positive? The accuracy of the model is the total number of persons correctly identified (true diseases positive plus true disease negative) out of the total people tested. F1 score is a harmonic mean of two factors i.e., precision and recall (or sensitivity). The performance of the model was measured by several factors including sensitivity, specificity, accuracy, and F1 score. False positive fractions and true positive fractions were used to demonstrate the ROC curve.

Table 1. Performance of the test statistics

Predicted Model	**Disease Detection**	**Normal**	**Total**
Predicted Model Positive	True Positive (TP)	False Positive (FP)	TP + FP
Predicted Model Negative	False Negative (FN)	True Negative (TN)	FN + TN
Total	TP + FN	FP + TN	TP + FP + FN + TN

- $\text{Sensitivity of Recall} = \text{TP}/(\text{TP} + \text{FN})$
- $\text{Specificity} = \text{TN}/(\text{FP} + \text{TN})$
- $\text{Positive Predictive Value or Precision} = \text{TP}/(\text{TP} + \text{FP})$
- $\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{FP} + \text{FN} + \text{TN})$
- $\text{Average of precision and recall F1 Score} = 2(\text{Recall} * \text{Precision})/(\text{Recall} + \text{Precision})$
- $\text{False Positive Fraction} = \text{FP}/(\text{FP} + \text{TN})$
- $\text{True Positive Fraction} = \text{TP}/(\text{TP} + \text{FN})$

4.3 Proposed Modules Requirement in Python:

- **VGG16:** It is an easy and broadly used Convolutional Neural Network (CNN) Architecture used for ImageNet which is a huge visible database mission utilized in visual object recognition software research.
- **Keras:** It is a Python module for deep learning that runs on top of the TensorFlow library. It was created to make implementing deep learning models as easy and fast as possible for research and development. The fact Because Keras runs on top of Keras we have to install TensorFlow first. To install this library, type the following commands in IDE/terminal.
- **SciPy:** SciPy is a free and open-source Python module used for technical and scientific computing. As we require Image Transformations in this article we have to install the SciPy module. To install this library, type the following command in IDE/terminal.
- **glob:** In Python, the glob module is used to retrieve files/pathnames matching a specified pattern. To find how many classes are present in our train dataset folder we use this module in this article.

4.4 Image quality enhancement

Raw input chest X-ray scans is low quality and also includes some noise, in this case for using recent techniques directly applied the deep learning models without quality enhancement. In this case, such methods may not be reliable for a longer time. The input chest X-ray image for consider pre-processed in the proposed using different methods in the recent literature namely adaptive intensity values adjustment, median filtering, and histogram equalization. This technique is mainly used to enhance the contrast:

$$I^1 = imadjust(I) \quad \dots (1)$$

where I^1 is an outcome of the contrast enhancement step using the function adjust.

Median filtering which is used to remove the noise in the contrast-enhanced image. In this case adjusting the image intensity values leads to noise and also an X-ray scan introduces the noise in the image. Median filtering shows effective enhancement in comparison to adaptive bilateral filtering [10], average filtering, and wiener filtering for X-ray datasets. The corresponding filtering classes as lightweight filtering techniques and many of the researchers is commonly used for image processing research. Median filtering of proposed model that works based on moving the image pixel by pixel and also replacing every value with the neighboring pixel's median value. It will be working based on neighbor's pattern is decided using the size of the window 3 × 3 neighborhood has been used in this work. The 2D median filter is applied on I1 as:

$$I^2(i,j) = medium \{I^2(i,j)(i,j) \in w\} \quad \dots (2)$$

where I^2 is an outcome of the median filtering and w is the size of the window.

The results of the median filtering or image enhancement model are working based on chest X-ray images and enhanced images as shown in Fig. 2 and Fig. 3. The outcome shows the source raw X-ray images converted into quality enhances optimal contrast and image quality and the process helps to accurately find the lung regions during the ROI extraction process.

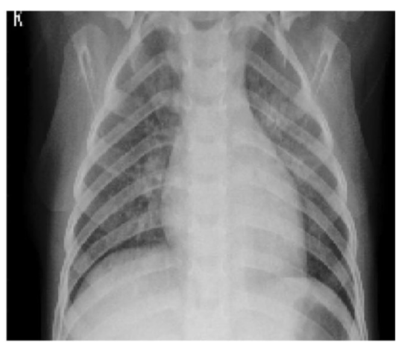

Fig. 2 Chest X-ray image

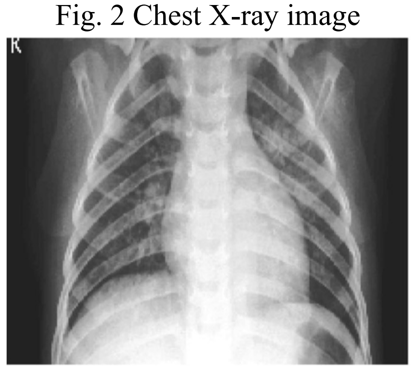

Fig. 3 Outcomes of chest X-ray image enhancement

4.5 Feature extraction and normalization

The region of interest (ROI) means extracted images have been used for processing the feature extraction image processing research. In this research different steps involved such as visual, texture, intensity, and geometric moment features. The iterations of the research mainly focused on visual features, which is used to extracted by the HOG descriptor. Researchers using different types of texture features have been extracted using the Gray level Co-occurrence Matrix (GLCM). In this case, 8 types of intensity features and geometric moment invariant features have been extracted using region of interest. ROI image includes total of 36 features are extracted called 4 HOG, 8 Intensity, 8 geometric moment, and 16 texture with accuracy enhancement and minimum computational efforts. In image processing research include various feature extraction techniques which is used to exploited for efficient learning and classification for improving the research enhancement such as scale-invariant feature transform, speeded-up robust features, discrete wavelet transform, and local binary patterns. Different stages of features extractions between illustrations of raw input chest X-ray image (Fig. 4) to enhanced chest X-ray image (Fig. 5) and finally converted into feature extracted chest X-ray image (Fig. 6).

Fig. 4 Illustrations of raw input chest X-ray image

Fig. 5 Illustrations of Enhanced chest X-ray image

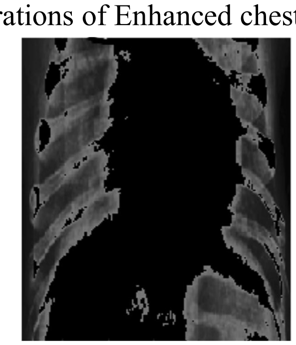

Fig. 6 Illustrations of feature extracted chest X-ray image.

4.6 Proposed model architecture

In this research, explain different steps of the proposed model for robust and efficient classification of disease from input chest X-ray images. Figures 6 show the proposed model architectures using soft computing, machine learning, and deep learning techniques which have been referred to as CNN and LSTM. LSTM is defined as long short-term memory networks with deep learning. It is another form of Recurrent Neural Networks (RNNs) that are capable of learning long-term dependencies for predicting effectively in the form of sequence prediction problems.

The proposed model shown in Fig. 7, explains the problem definition and its different stages of raw Chest X-ray images, enhances the quality of raw X-ray images, extracts the ROI of lung regions, feature extraction, features fusion and normalization, and finally predict pneumonia diseases either positive or negative using soft computing and machine learning methods for detection and classification. The proposed model for using different pretrained techniques are SVM, ANN, Ensemble, and KNN used as input and return the detection outcome which is used to perform the comparations. The proposed model includes pre-trained databases has been used during the estimation process, which include sequential features of the input images learned with pre-trained DB and estimated the probability with minimum processing time. The proposed design of the deep training and detection model helps to reduce both training and testing time in comparison to other image processing models.

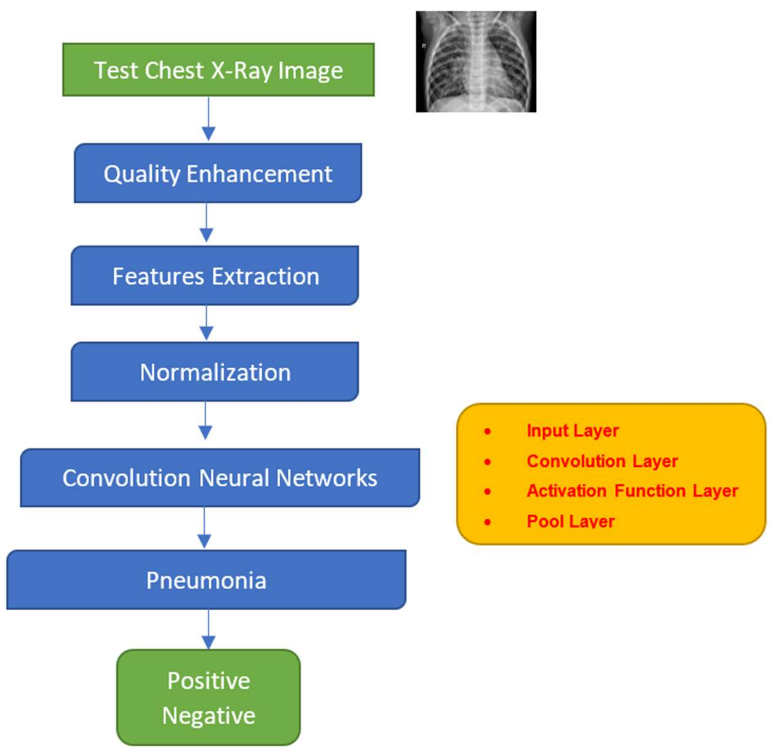

Fig. 7 Architecture of the proposed system for lung disease detection

4.7 Stepwise Implementation

Step 1. Download the corresponding dataset from the Kaggle website [21] and the dataset which contains a test, train, and validation.

Step 2. Import the python necessary packages in VGG16, Keras, SciPy, and glob.

Step 3. X-ray image resizes in the form of 224 x 224 this is a fixed-size using VGG16 architecture.

Step 4. Import the python package VGG16, which is used to classify the different categories present in *imageNet*. In this case, our problems are divided into two categories Pneumonia and Normal.

Step 5. Import the famous python model namely *VGG16*. This package is used to form the loop iteration of entire layers and set the trainable as the false state. In some cases, all the layers would not be trained.

Step 6. **In this stage perform to find** how many classes are present in training data and also find how many output labels.

Step 7. In this step is used to make a flattened layer and also add the last layer activation function. After that *len(classes)* function is used to categorize the output layer.

Step 8. Finally, the VGG python package is used to predict the outcomes.

Step 9. The above steps are completed then compile our model using *adam* optimizer. The optimization metric is also performed in this stage, which is used to find accuracy.

Step 10. The model compilation process is completed, then the corresponding data has to import to Keras using ImageDataGenerator. In addition, various metrics also support these steps which are used to rescale the data and it will help us in the training and testing stages.

Step 11. To feed the images using *the flow_from_directory()* function. Batch size 4 indicates that at once 4 images will be given for training. Finally, the Class_mode is Categorical whether the x-ray images are either Pneumonia or normal.

Step 12. Similarly, the same iterative process will do the same steps for testing the dataset.

Step 13. Finally, the proposed model is to be fitted using *the fit_generator()* function and pass all the necessary details regarding our training and testing dataset. This will take some time to execute.

Step 14. Create a model file and store this model.

Step 15. Load the model. Now read an image and preprocess the image. Finally, check what output our model is giving using the *model. predict()* function.

5. Result and discussions

Numerical illustrations are used to explain the proposed models with table and graphs for easy to understand the concepts. In this section, which is used to presents the experimental results and their model performance and evaluation of the proposed lung disease detection outcomes are categorized whether chest X-ray images for pneumonia or normal. The proposed model was implemented using Python for publicly available lung disease datasets on the Kaggle repository [21]. The proposed model CNN-LSTM is compared to different similar studies with accuracy and training and detection time. The dataset contains 5856 samples in two classes and the model predicts the outcome called pneumonia or normal. In this case the predicted number of samples was normal (1583) and pneumonia (4273). In this model taking consideration into the raw datasets are divided into 70% as training data and 30% as a testing data for the analysis of proposed system. Various numerical illustrations for use in these sections which is used to prove the results and discussions using tables 3, table 4, table 5 and table 6 subsequently explain the same through figure 9, figure 10, figure 11, figure 12 and figure 13. The proposed system has been analyzed and predicted using the familiar detection accuracy namely F1-score, precision, recall, and specificity. The comparative analysis with the existing methods through accuracy and computational time.

Table 2: Dataset and their splitting

Total chest X-ray images	5856
Normal chest X-ray images	1583
Pneumonia chest X-ray images	4273
Training samples (70%)	4099
Testing samples (30%)	1756

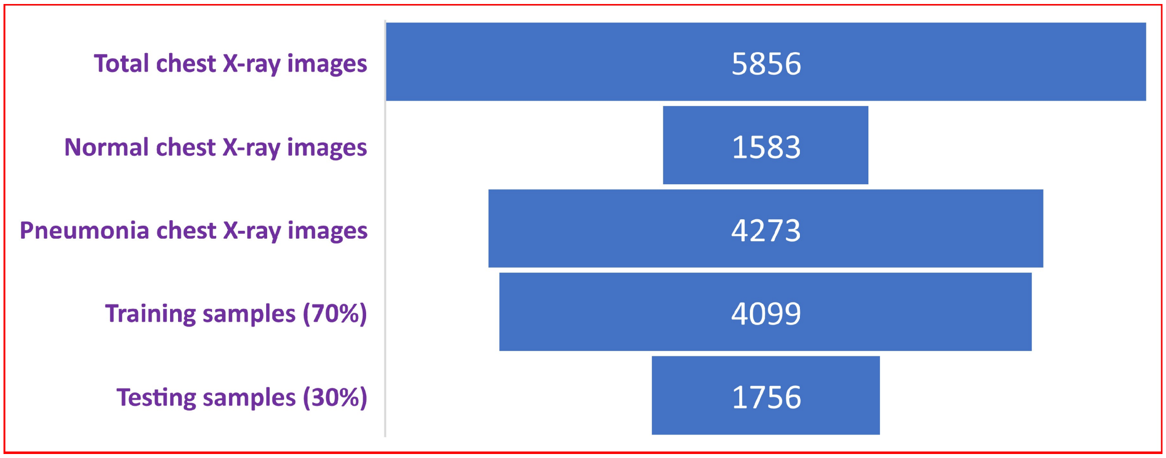

Fig. 8. Dataset and their splitting

The experiments and their accuracy performance of the proposed system using different soft computing techniques namely K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Artificial Neural Network (ANN), Ensemble, and Convolutional Neural Network-Long Short Term Memory Network (CNN-LSTM) which is used to demonstrate the detection accuracy, precision, recall, specificity, and F1score respectively. The results and discussion demonstrate the outcomes through soft computing techniques and feature normalization methods using the proposed computer vision approaches for image enhancement and ROI extraction methods for the dataset.

Based on different features normalization techniques, the robust feature normalization techniques delivered an accuracy performance parameter namely accuracy, precision, recall, specificity, and F1-score metrics compared to raw features and min–max normalization techniques. The proposed method considers the raw features without applying any feature normalization with poor classification performance compared to max-min normalization. Compared to the max-min normalization, having poor performance compared to robust normalization. The related performance and their detection accuracy using similar trend has been observed for accuracy performance shown in table 3 and figure 9, precision shown in table 4 and figure 10, recall shown in table 5 and figure 11.

Table 3 Comparative Analysis of Accuracy Performance

Classifier	Raw Features	Max-Min Normalization	Robust Normalization
KNN	83.45	84.13	87.74
SVM	83.89	86.95	89.75
ANN	90.12	91.22	93.47
ENSEMBLE	87.85	89.54	89.63
Proposed Model	91.58	95.45	97.12

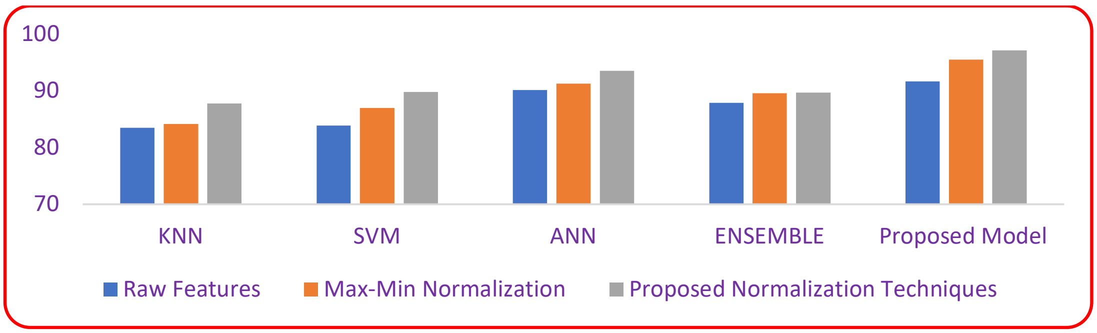

Fig. 9 Comparative Analysis of Accuracy Performance

Table 4: Comparative Analysis of Precision Performance

Classifier	Raw Features	Max-Min Normalization	Robust Normalization
KNN	77.52	79.23	85.12
SVM	75.42	80.45	86.11
ANN	81.74	85.12	90.74
ENSEMBLE	82.13	84.74	86.45
Proposed Model	89.23	94.23	94.78

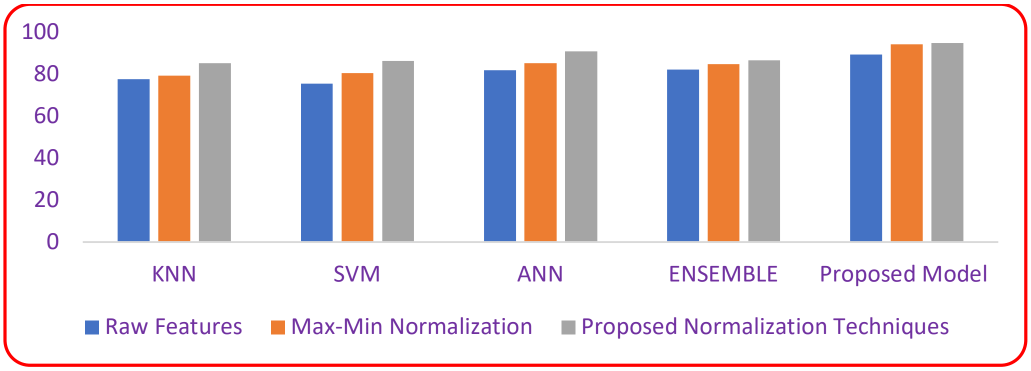

Fig. 10 Comparative Analysis of Precision Performance

Table 5: Comparative Analysis of Recall Performance

Classifier	Raw Features	Existing Normalization	Proposed Normalization
KNN	89.17	90.13	93.14
SVM	89.75	91.41	89.45
ANN	92.45	94.47	95.64
ENSEMBLE	83.88	90.85	90.78
Proposed Model	92.88	96.87	98.78

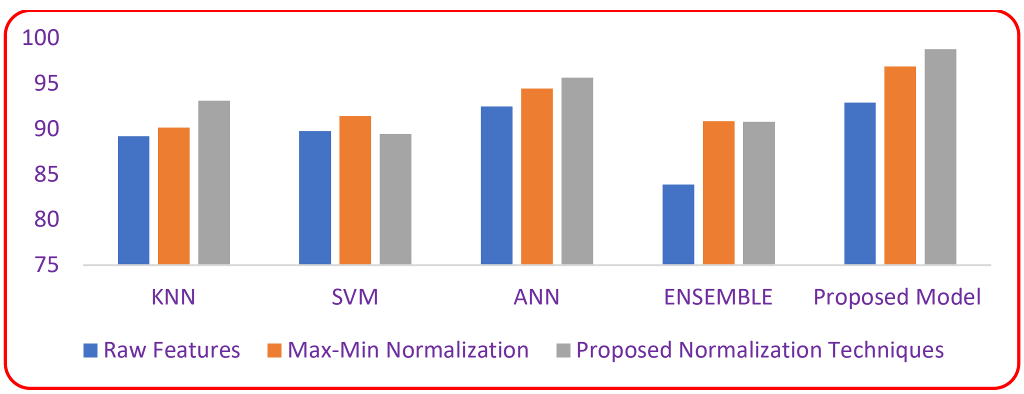

Fig. 11 Comparative Analysis of Recall Performance

In this paper clearly explain, we have proposed an approach to find the lung disease detection from the preprocessed chest X-ray images and pneumonia classification either positive or normal. The proposed model which is used to find specific features only by considering the image enhancement followed by ROI-based feature extraction and normalization. In this case, the enhance the classification performance with minimum time requirement. Based on numerical illustrations, proposed a deep learning model CNN-LSTM with soft computing and machine learning techniques such as SVM, ANN, and KNN as well as for CNN-LSTM using the publically available datasets. The related comparative studies focused on various review of literature mentioned in table 6 for pneumonia detection accuracy and their training and detection time shown in table 6, figure 12 and figure 13.

Table 6 Comparative analysis for detection accuracy, training and detection time

Existing Methods	Literature Review	Detection Accuracy	Detection Time (Seconds)
CDD-CNN	[22]	88.23	4083
CDDL	[26]	92.54	3872
COVIDetectioNet	[27]	90.73	3264
CNN-RN	[23]	92.05	4599
ResNeXt-50	[25]	91.09	4379
CNN-E	[24]	92.04	3572
Proposed Method		96.31	1682

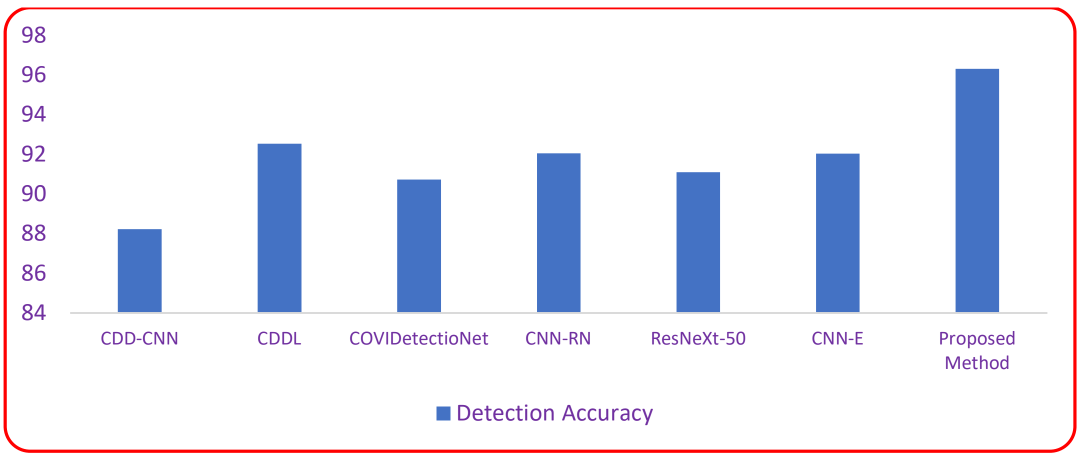

Fig. 12 Comparative analysis for detection accuracy

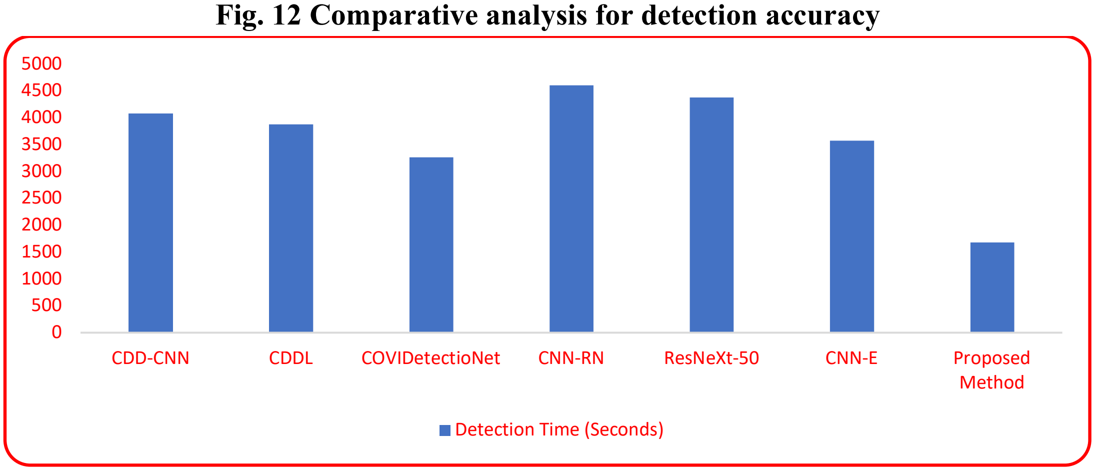

Fig. 13 Comparative analysis for detection accuracy with time in seconds

5. Conclusions

In this research work, the proposed method was achieved using deep learning-based approaches. The proposed system had a high accuracy for identification of cases with pneumonia, and normal conditions. In this model, which is used to classify the results of the deep learning model indicate that this model can be helpful for the medical field. In future, the proposed system have automated classification detection techniques in the form of GUI which is used to medical professionals to detect the information on time.

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