Article

Fusion of Deep Convolutional Neural Network with PCA and Logistic Regression for diagnosis of pediatric pneumonia on chest X-Rays

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Received 4 May 2020; *Accepted 31 May 2020*; *Published 1 September 2020*

Abstract

Consistent headway in machine learning technology is gradually substantiating its significance in many areas of medical research. Pneumonia is a disease caused due to acute respiratory infection affecting one or both lungs. Diagnosis and treatment of pneumonia at early stage can increase the survivability of suffering patients. Computer Aided Diagnosis (CAD) techniques are bridging up the gap of medical science and computer science by successfully diagnosing diseases such as tumor, cancer, pneumonia etc. This paper proposes a fusion of Deep Convolutional Neural Network Model with Principal Component Analysis (PCA) feature extraction model and Logistic Regression (LR) classifiers for the diagnosis of pneumonia from chest X-ray images. In this study, fine-tuned pre-trained CheXNet model is used as Convolutional Neural Network (CNN) model on standard pneumonia dataset collected from Guangzhou Women and Children's Medical Center, Guangzhou. The proposed model is capable of detecting pneumonia with an accuracy which outperforms the existing methods from 0.8% to 21.9% approx. Comparison with existing models and methods reveal that the proposed model delivers superior results than others according to precision, f1-score, accuracy and AUC values. This research can be a great subsidiary for radiologists or medical researchers for diagnosis of pediatric pneumonia from chest X-ray images.

Keywords AUC; CheXNet; computer aided diagnosis; Convolutional Neural Network; Logistic Regression; PCA; pneumonia; ROC.

Network Biology
ISSN 2220-8879
URL: http://www.iaees.org/publications/journals/nb/online-version.asp
RSS: http://www.iaees.org/publications/journals/nb/rss.xml
E-mail: networkbiology@iaees.org
Editor-in-Chief: WenJun Zhang
Publisher: International Academy of Ecology and Environmental Sciences

1 Introduction

CNN-motivated Deep Learning with its incremental growth as CAD is making the radiologists task spontaneous. Modern technology has made diagnosis and treatment easier and more convenient than before.

The availability of large datasets and unbeatable success of deep learning has made diagnosis task more accurate.

Every year in the United States, more than 600,000 (15%) adults are hospitalized and approximately 4 million are diagnosed with pneumonia which is the major cause of morbidity and mortality (Auble et al., 2015). From a report of CDC (2017), due to pneumonia, more than 250,000 people are hospitalized and around 50,000 die every year in the US alone (CDC, 2017). Pneumonia can be mild to severe and is still one of the leading causes of child death. This severe inflammatory disease can be caused by virus, bacteria or fungi. According to the World Health Organization (WHO), pneumonia is the most significant cause of pediatric death killing around 2 million children under 5 years of age every year (Rudan et al., 2008). Pneumonia is an infectious disease of lungs that inflames the lungs alveoli filling them with pus and fluid which can cause shortness of breath, chest pain, fever, cough, fatigue, vomiting or diarrhea etc. Pneumonia can be categorized as typical pneumonia, atypical pneumonia, bronchial pneumonia, lobar pneumonia etc. and likely to occurring more on air polluted and developing countries where older, children, smokers and patients with other diseases are on high risk zone. Based on patients' medical conditions different methods can be used to diagnose pneumonia such as chest X-ray or chest radiography, blood test, sputum culture, pulse oximetry, chest CT scan, bronchoscopy, pleural fluid culture etc (Pneumonia, 2020).

Chest X-ray is one of the most commonly used painless and non-invasive radiological tests to screen and diagnose many lung diseases also other methods such as CT and MRI can be used (Liang and Zheng, 2019). In clinical diagnostics about one-third of all radiological examinations are made up of chest X-rays or chest radiographs (CXRs) (Chauhan et al., 2014). Chest X-ray is used in emergency diagnosis and treatment of lungs, hearts and chest wall diseases as it is fast and easy (Radiology, 2020). Deep learning plays an important role for the diagnosis and treatment of diseases. Before taking any final decision about the diagnosis of a disease, radiologists can get a second opinion from CAD tools (Chauhan et al., 2014). This study employs CAD method to diagnose pneumonia from chest X-ray dataset. The dataset of Kermany et al. (2018) from Guangzhou Women and Children's Medical Center, Guangzhou contains 5,856 X-ray images of pediatric patients of one to five years old. After some preprocessing of the images, image augmentation is applied to increase the number of trainable images.

The National Institutes of Health (NIH) CXR dataset released by (Wang et al., 2017) is comprised of 112,120 frontal CXRs, individually labeled to include up to 14 different diseases. For creating these labels from the associated radiological reports, the authors used Natural Language Processing to text-mine disease classifications whose expected accuracy is more than 90%. CheXNet is a model proposed by the researchers from Stanford University that uses this NIH CXR dataset and is said to exceed the average radiologist performance on the pneumonia detection task (Rajpurkar et al., 2017). CheXNet model uses pretrained ImageNet weights and is based on DenseNet121 deep CNN model which can detect the presence of 14 different diseases (Liang and Zheng, 2019).

In this paper, a deep CNN model is proposed with transfer learning and fine tuning that uses CheXNet weights. PCA and Logistic Regression techniques are then applied on the model features to build the final pneumonia detection model. The proposed final model outperforms CheXNet and other existing models for pneumonia detection from Chest X-ray images. Before feeding the images to CNN model some preprocessing is performed to the chest X-ray images.

The rest of the paper is organized as follows: The proposed material and methods of this study is portrayed in section 2. Section 3 describes and analyses the research results. Finally, section 4 briefly discusses the steps and performances of the proposed method.

2 Material and Methods

This section presents the detailed steps of the proposed pneumonia detection method. From data collection to model evaluation several experimental steps are performed as shown in Fig. 1. Fine-tuned CheXNet model with transfer learning is used here as both a classification and feature extraction model. Afterward, SVM and PCA with Logistic Regression are used on the deep CNN features to classify pneumonia chest X-ray images.

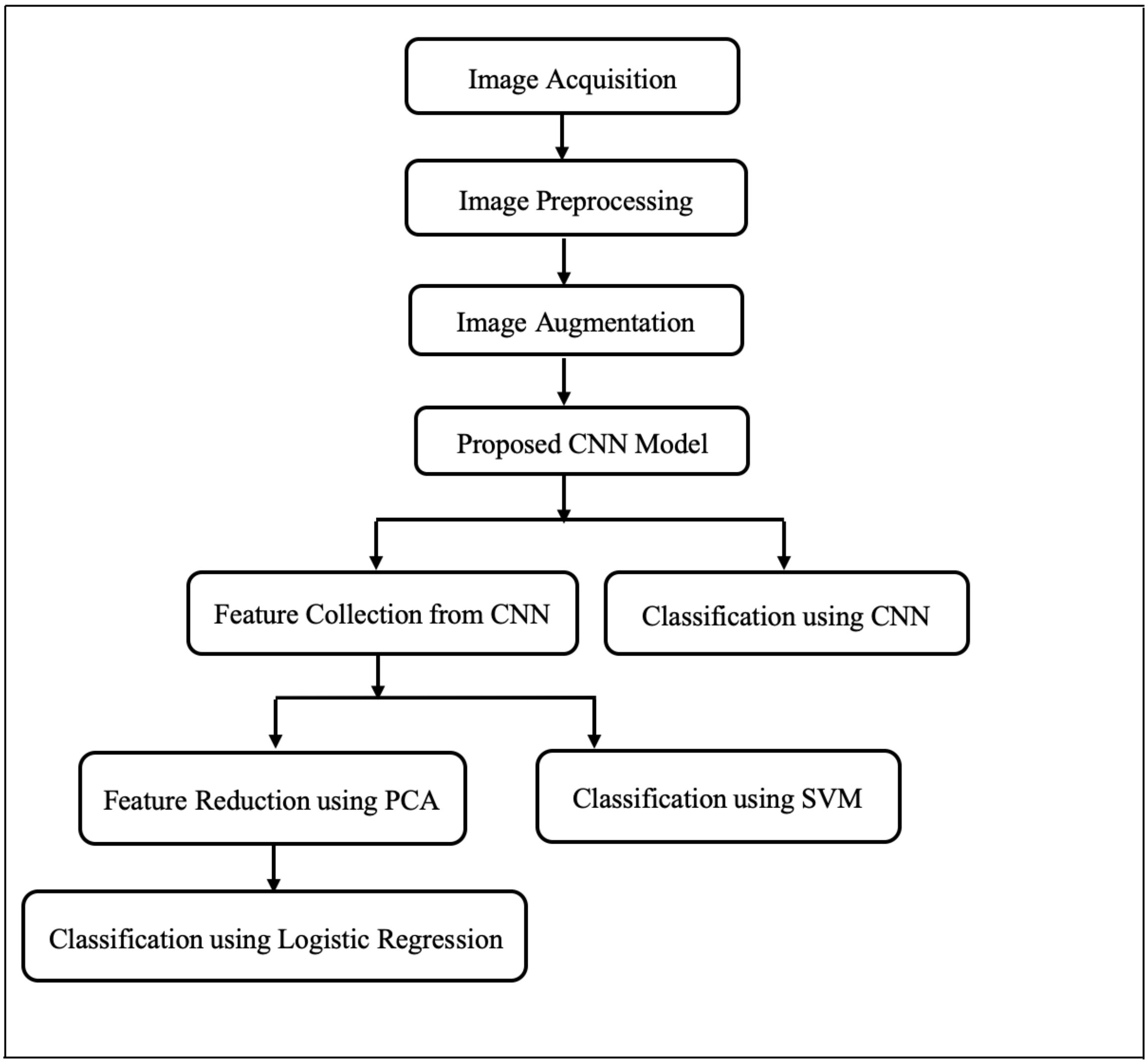

Fig. 1 Schematic representation of pneumonia detection method.

2.1 Image acquisition

Before going to any further details, it is important to specifically describe the dataset used in this study. The original dataset introduced by (Kermany et al., 2018) contains 5856 chest X-ray images collected by X-ray scanning of pediatric patients between 1 and 5 years old from Guangzhou Women and children's Medical Center. To confirm a diagnosis, the radiographs are interpreted and then referral decisions are made (Rajaraman et al., 2019). The dataset is organized as three folders train, test and validation where each containing two sub-folders naming normal and pneumonia and there are total 1583 normal images and 4273 pneumonia images in the dataset. Fig. 2 shows an outline of the dataset. Here, in this study test dataset is used for validation also, because there are only 16 validation images given, 8 for normal and 8 for pneumonia patients.

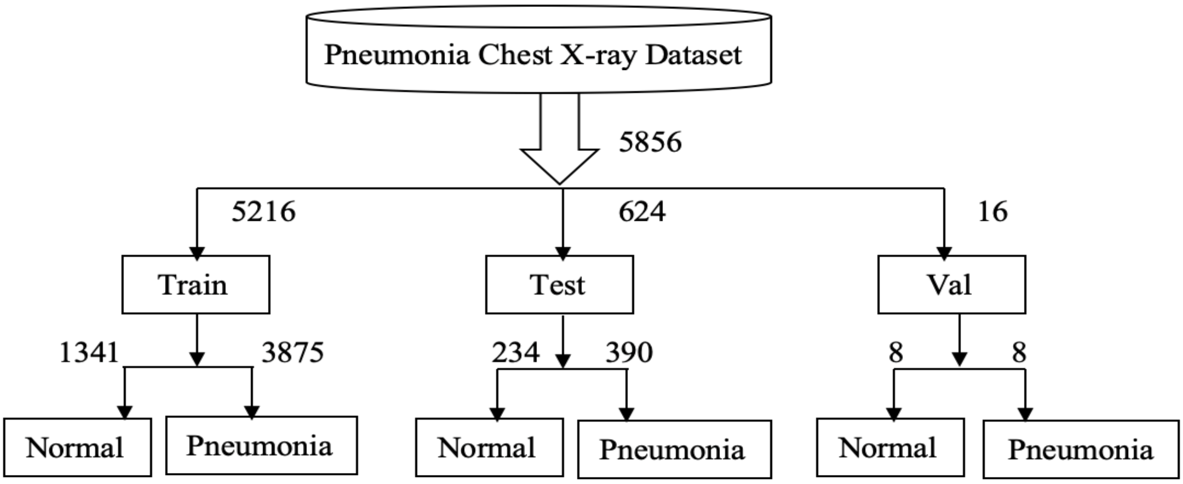

Fig. 2 Schematic outline of chest X-ray image dataset.

2.2 Image preprocessing

The X-ray images of the dataset are pre-processed before using. Different pre-processing techniques are used by authors in many studies with varying accuracy. In this research, Chest X-ray images are downscaled to 224×224 keeping the RGB channels intact because CheXNet takes input images of size 224×224. Then Adaptive Histogram Equalization technique as an excellent contrast enhancement method is applied to the images. It's automatic operation and effective presentation in medical imaging has made it a competitor to the standard contrast enhancement method.

Table 1 Geometric translation as augmentation technique.

Methods	Corresponding values	Descriptions
Rescale	1/255	Used to rescale the images in the range of [0,1].
Shear Range	0.2	Shear angle in counterclockwise direction. Used in both train and test dataset.
Zoom Range	0.2	Random zooming range.
Width Shift	0.1	Random horizontal shift range.
Height Shift	0.1	Random vertical shift range.
Horizontal Flip	True	Horizontal flipping of images.

2.3 Image augmentation

Deep CNN requires a large amount of training data otherwise it may overfit and tends to be less accurate. To artificially increase the size and quality of training data, prevent overfitting problem and enhance the model's generalization ability during training, data augmentation technique is often applied in classification problems Stephen et al. (2019) got augmented data by applying some geometric translations such as rescale, shear range, zoom range, width shift range, high shift range and horizontal flip each of which are shown in Table 1 with their corresponding values. The images are then labeled to 0 and 1 for normal and pneumonia images accordingly.

2.4 Proposed CNN model

The proposed CNN model is used here as a feature extractor and also as a classifier for pneumonia detection. This study uses fine-tuned, pre-trained, ChexNet model which in turn uses pre-trained 121-layer DenseNet model. In Dense Convolutional Network (DenseNet), each layer connects to every other layer in a feed-forward fashion (Huang et al., 2017). Each Dense block consists of Batch Normalization, ReLU Activation and 3×3 Convolution. Fig. 3 displays the proposed model. To fine tune CheXNet model, classifier part along with the average pool part of the model is discarded and then a 20% dropout and flatten layer followed by a max pool layer is added to the model. The fine-tuned model also uses three dense layers with 512, 128 and 64 neurons. Each of these dense layers has a dropout rate of 70, 50 and 30 percent to prevent overfitting problem. From the dense layer containing 64 neurons, CNN features are extracted for further processing. As diagnosis of pneumonia is a binary classification problem, the model uses sigmoid as an activation function at the final layer except that all activation layer use ReLU activation function. The model uses Adam optimizer and binary cross entropy loss function. If the validation loss plateaus till 4 epochs, the learning rate is decayed by a factor of 0.5. Each time callbacks check the model's internal states during training and save the best performing model. Model is trained end-to-end with a mini batch size of 32. Validation accuracy and test accuracy are calculated as the performance measure of the model. For comparison with other models AUC (Area Under the ROC) values are also estimated from ROC (Receiver Operator Characteristic) curve.

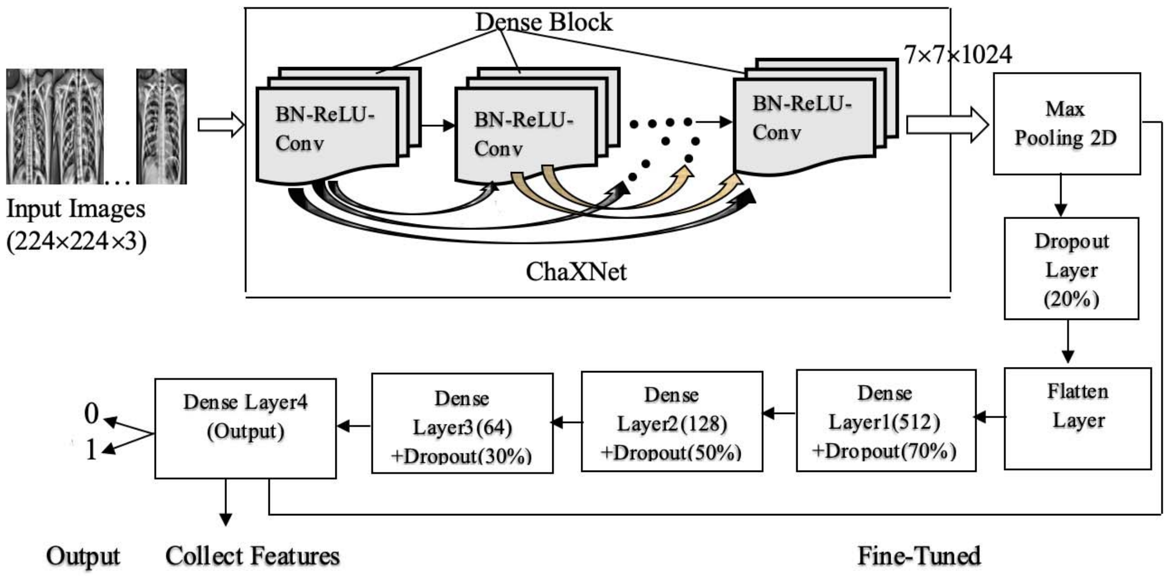

Fig. 3 Architecture of the fine-tuned proposed model.

2.5 Feature reduction

From the last Dense layer, before the output layer CNN features are collected. The collected features of the whole image dataset are then combined and stored in a csv file. To reduce the feature space dimensionality, different methods can be used. PCA is a feature reduction method which uses feature extraction technique rather than feature elimination technique (Zhang, 2010, 2011). Features dataset is then split into training and testing dataset keeping 11% data as test data. PCA is applied to both the train and test dataset with two principal components PC1 and PC2 respectively.

2.6 Pneumonia classification

For the diagnosis of pneumonia, three classification techniques are used in this research. They are described through the subsections 2.6.1 to 2.6.3 as follows.

2.6.1 Pneumonia classification using Deep CNN

The proposed deep CNN architecture has already been discussed in section 2.4. The output dense layer of the model uses sigmoid activation function which classifies normal X-ray images as 0 and pneumonia affected images as 1.

2.6.2 Pneumonia classification using Logistic Regression (LR)

Logistic regression is a statistical term which is now widely used in machine learning. It is an appropriate regression method for binary classification problem. In this study, logistic regression is used after applying PCA to identify normal images and pneumonia affected images.

2.6.3 Pneumonia classification using Support Vector Machines (SVM)

Srivastava et al. (2010) mentioned that, the SVM (Support Vector Machines) are generally capable of delivering higher classification accuracy than the other data classification algorithms. Unlike CNN models, SVM does not require a huge amount of training data. It is fast and one of the most efficient binary classification methods in machine learning. SVM is applied on the collected CNN features for the detection and classification of pneumonia X-ray images.

3 Results

This section discusses about the experimental results of each method, evaluation strategy, evaluation parameters, validation and test accuracy and comparison with other pneumonia detection models.

3.1 Image acquisition, preprocessing and augmentation

After the collection of (Kermany et al., 2018) chest X-ray images, image preprocessing techniques such as resizing and adaptive histogram equalization are applied to the images. The original and preprocessed images are displayed in Fig. 4. Then to resolve the overfitting problem and increase the size of training data, augmentation is performed. For the evaluation of test accuracy test data needs to be labeled to 0 and 1. This labeling is also done in augmentation steps (section 2.3).

3.2 Performance evaluation parameters

Before evaluating the overall performance from test dataset, model is trained with the training dataset along with hyperparameters tuning to enhance the performance on the validation set (Rudan et al., 2004). The proposed model is compared with other models in terms of validation accuracy, test accuracy, precision, recall/sensitivity, f1-score, Receiver Operator Characteristic Curve (ROC) and area under the ROC (AUC) values.

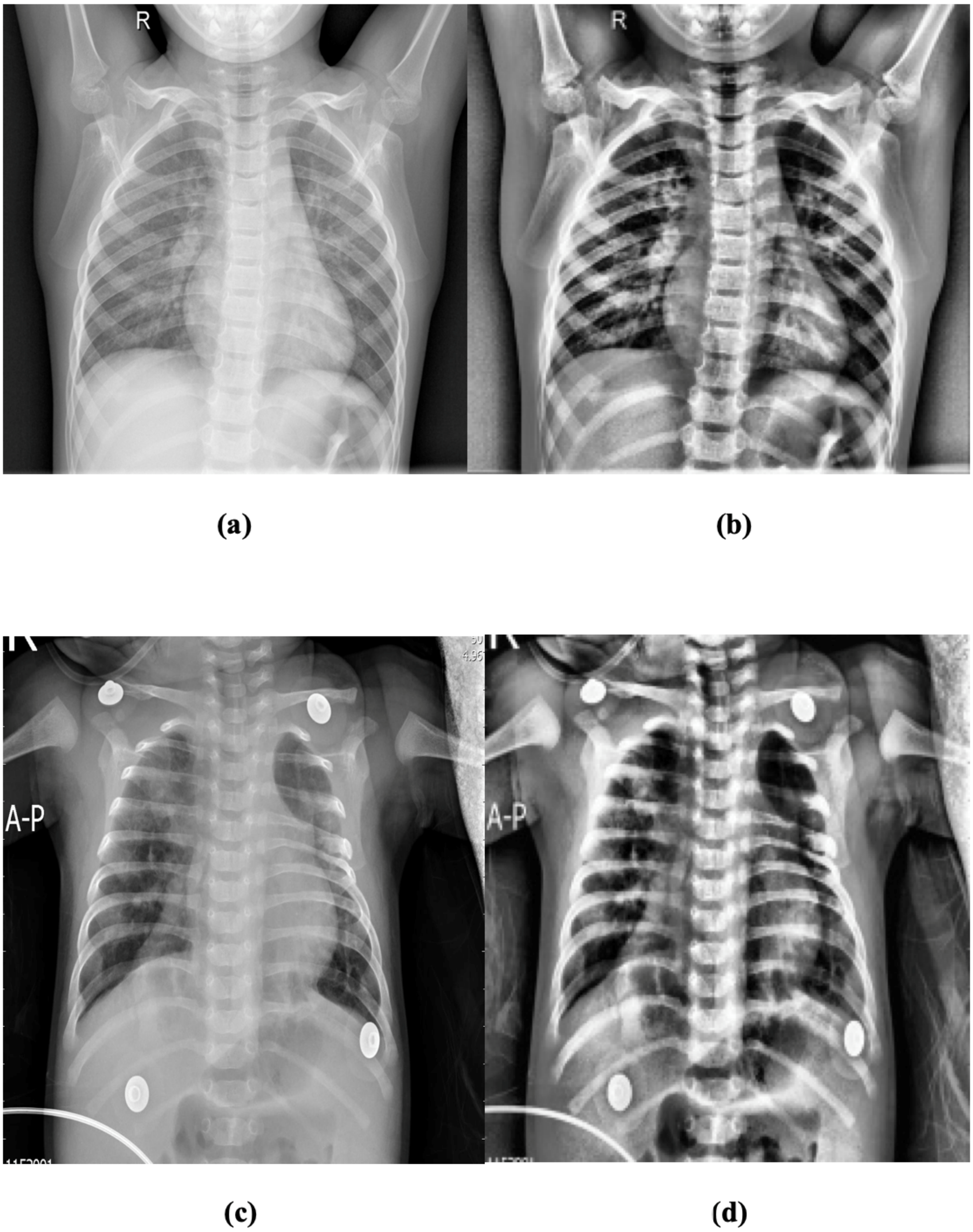

Fig. 4 Illustrative example of original (a) normal (c) pneumonia image and corresponding preprocessed images are (b) and (d).

For computing these performance metrics, four performance parameters - True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are used. TP is the prediction of a positive class as positive. TN is the prediction of a negative class as negative. FP is the prediction of a negative class as positive. And FN is the prediction of a positive class as negative.

The following formulae are used to calculate the performance metrices.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall/Sensitivity} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-score} = \frac{2*Recall*Precision}{Recall+Precision} \quad (4)$$

$$\text{TPR} = \text{Recall} = \frac{TP}{TP+FN} \quad (5)$$

$$\text{FPR} = \frac{FP}{FP+TN} \quad (6)$$

ROC is a visual representation showing the True Positive Rate (TPR) (y-axis) against the False Positive Rate (FPR) (x-axis). It is an important and valuable method in evaluating the uncertainty and distinguishing the strengths and weaknesses of diagnostic tests (Junge et al., 2018). Through AUC score, successful prediction rate of different models can be compared.

A confusion matrix is a table showing all of the four performance measures (TP, TN, FP, FN) of a model while performing classification. It shows both the number of correctly predicted and incorrectly predicted results of a model. The confusion matrix of the proposed model will be mentioned in later section of the paper.

Cross Validation (CV) is a statistical technique used to measure the effectiveness of a model and to reduce the overfitting problems (Zhang, 2010). It gives an indication of how well a model would generalize to an independent data set. Two types of cross validation techniques (Train Test Split (TTS) CV and K-Fold CV) are performed in this research. In TTS, the entire dataset is randomly split into train and test set where training and testing are performed on corresponding train and test data. K-Fold CV splits the dataset into a number of k folds where each time one-fold acts as a test dataset and the remaining folds are training dataset. This process continues until all the folds served as the test dataset.

3.3 Proposed CNN model implementation and evaluation

All of the methods and algorithms including training and testing performed in this experiment were done with keras framework (using tensorflow backend) in python on a mac operating system using google colab gpu. The proposed model uses fixed image input size of 224×224. The hyperparameters of the model were tuned based on the effectiveness of the validation dataset during training. The test accuracy of the model is then computed according to the test dataset. The model achieves a validation accuracy of 93.07% with 92.63% test accuracy which is better than the existing models. The comparison section (3.4) discusses all other performance measure parameters of this study.

3.4 Comparison with other models and works

Our proposed model is able to achieve approximately 93% test accuracy. This model is then compared with existing models- VGG16, ResNet, DenseNet121, InceptionV3, Xception which are most frequently used CNN models for medical image classification. Liang and Zheng (2019) mentions the performance parameters of the models VGG16, DenseNet121, InceptionV3 and Xception and from the paper (Chhikara et al., 2020) performance parameters of ResNet is also found. A visualization of the performances of each of these models on pneumonia dataset, based on precision, recall, f1-score and test accuracy using equation 1,2,3,4 is displayed in Table 2.

Table 2 Comparison of performance parameters among proposed model and existing models

Model	Precision	Recall	F1-score	Test Accuracy
VGG16	0.723	0.951	0.822	0.742
ResNet	0.742	0.961	0.837	0.783
DenseNet121	0.792	0.964	0.869	0.819
InceptionV3	0.916	0.841	0.877	0.853
Xception	0.857	0.967	0.908	0.878
Proposed Model	**0.928**	**0.956**	**0.941**	**0.926**

Table 2 clearly discerns the fact that the proposed CNN model gives much better performances than the compared five models in terms of precision, f1-score and test accuracy. So, it can be said that the classification accuracy of the proposed model outperforms VGG16, ResNet, DenseNet121, InceptionV3 and Xception by 18.4%, 14.3%, 10.7%, 7.3% and 4.8%.

Confusion matrix (CM) of the proposed CNN model is visualized in Table 3.

Table 3 Confusion matrix of the proposed CNN Model on chest X-ray dataset

True Label	Predicted Label	
	Normal (0)	**Pneumonia (1)**
Normal (0)	205 (TN)	29 (FP)
Pneumonia (1)	17 (FN)	373 (TP)

According to the CM, among the 624 test images, proposed model correctly classifies 578 images and misclassifies 46 images.

The models proposed on paper (Liang and Zheng, 2019) and paper (Chhikara et al., 2020) shows that their models perform better than the compared existing models used in this study. So, a comparison among our proposed model, with these two models along with a fine-tuned VGG19 transfer learning model is made in Table 4.

Table 4 Comparison with existing methods and pre-trained VGG19 fine-tuned model for pneumonia classification on Kemany et al. dataset.

Model	Precision	Recall	F1-score	Test Accuracy	CM	
Pre-trained fine-tuned VGG19	0.861	0.987	0.919	0.893	172	62
					5	385
Chhikara et al. (2020)	0.907	0.957	0.931	0.901	195	39
					17	383
Liang et al. (2019)	0.891	0.967	0.927	0.905	188	46
					13	377
Proposed Model	**0.928**	**0.956**	**0.941**	**0.926**	**205**	**29**
					17	**373**

Also, in this comparison, our model achieves 0.33%, 0.25% and 0.21% superiority than the compared models. Precision and F1-score are also better than the other three.

This study uses a fusion strategy for the diagnostic of pneumonia more effectively and accurately. Two types of fusion are used – CNN+SVM and CNN+PCA+LR. CNN features are collected from the dense layer before the output layer of the proposed CNN model into a feature vector. SVM is a classifier that produces significant accuracy using a separating hyperplane which separates classes. SVM tries to maintain maximum distances between datapoints of both classes using the hyperplane (Hasan et al., 2020). This study uses a linear SVM kernel, so a straight line is used to classify the classes. SVM detects pneumonia from the CNN features with an average accuracy of 95.61%. Thus, accuracy of the proposed model increases from 92.63% to 95.61%. Now as a second fusion method PCA and LR techniques are applied to the CNN features. Because, along with the important features, feature vector also holds some noisy information which can hamper model effectiveness. So, PCA as a feature reduction method is applied, which reduces the redundant features by transforming correlated features into independent features called principle components.

Top two principal components PC1 and PC2 are extracted as they provide the maximum variance. The reduced feature vector is then fed to LR for classification. LR is a well-defined model mostly appropriate for binary classification problem. LR produces an average accuracy of 96.08%. For experimental purposes after PCA, as a classifiers SVM is also applied which achieves an average accuracy of 95.33%. But PCA+LR model is chosen for providing better response towards the test dataset. Fig. 5 shows PC1 and PC2 with LR classifiers response on training and testing dataset. In the figure the points are true observation classes with two color for each class and the two-color regions are based on classifier observation. In the training set of Fig. 5 (a), some of the points overlap with each other as the classifier observation for those points are wrong. So, the classifier misclassifies them. For this reason, the classifier also misclassifies some points in test dataset as shown in Fig. 5 (b).

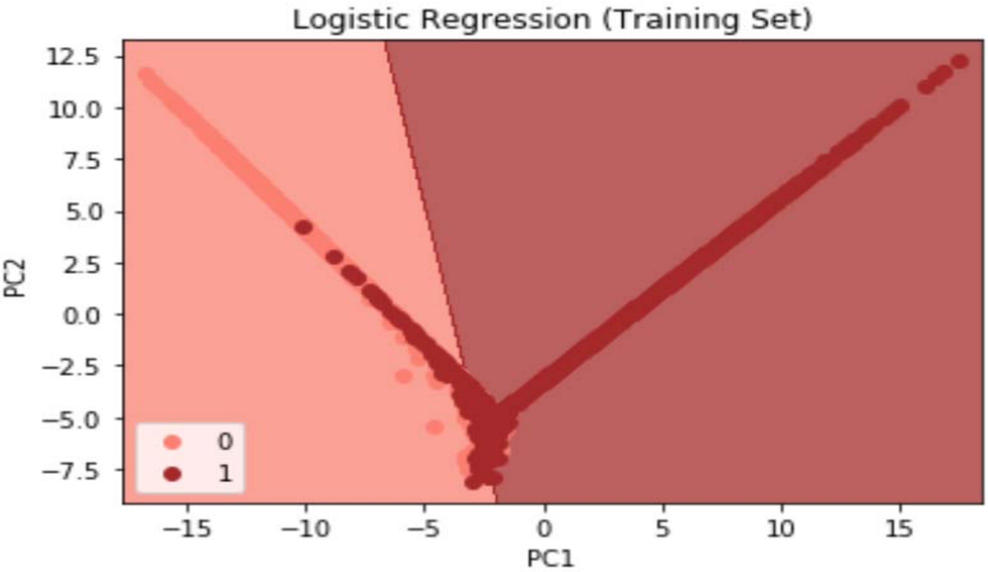

Fig. 5 (a) PCA and LR on training dataset.

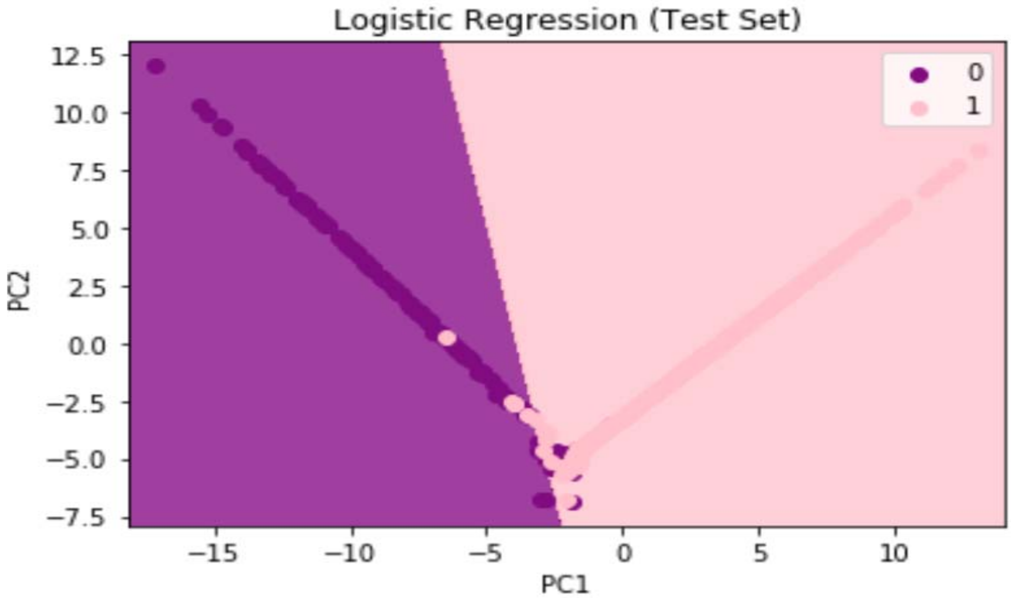

Fig. 5 (b) PCA and LR on test dataset.

Cross-validation is a model estimation technique defining a model's behavior toward an independent set of data. Here, two CV techniques Train-Test Split (TTS) and K-Folds are used up to 5 folds. Comparing to K-Fold CV, TTS CV performed better here. The feature vector dataset is shuffled and divided into training and test dataset using train test split with a little test size of 11% to make the dataset organization similar to the original dataset. Then SVM, PCA+SVM and PCA+LR techniques are applied on the dataset for 5 folds. Tables 5 and 6 display the comparative performances of each of the described method for each fold with mean accuracy.

Table 5 Comparative performances of different models using K-Fold CV.

CV Folds	Methods		
	CNN+SVM	CNN+PCA+SVM	**CNN+PCA+LR**
Fold 1	0.955	0.941	**0.961**
Fold 2	0.956	0.961	**0.957**
Fold 3	0.952	0.952	**0.955**
Fold 4	0.962	0.954	**0.955**
Fold 5	0.967	0.949	**0.952**
Average Accuracy	0.959	0.952	**0.956**

Table 5 and Table 6 assures that K-Fold CV performs well for CNN+SVM model while TTS CV performs more accurate for the other two models. For both of the CV, mean accuracy is granted as the model accuracy. Table 6 founds that proposed final model (CNN+PCA+LR) achieves at most 97.5% accuracy in fold 3, which is the maximum pneumonia classification accuracy till now.

Table 6 Comparative performances of different models using train test split CV.

CV Folds	Methods		
	CNN+SVM	CNN+PCA+SVM	**CNN+PCA+LR**
Fold 1	0.955	0.958	**0.952**
Fold 2	0.969	0.961	**0.961**
Fold 3	0.949	0.946	**0.975**
Fold 4	0.958	0.958	**0.961**
Fold 5	0.950	0.944	**0.955**
Average Accuracy	0.956	0.953	**0.961**

Stephen et al. (2019) proposed a CNN model from scratch for classification of chest X-ray pneumonia images. The model provides 93.73% validation accuracy. Another study by Saraiva et al. (2019) proposed a CNN model for pneumonia classification which uses K-Fold CV. This model shows an average accuracy of 95.30%. Both of the model has used (Kermany et al., 2018) dataset for their classification task.

So, comparing our proposed final model with these two and from the previous comparison with other models proved our model as the best pneumonia classification model achieving 96.1% average test accuracy.

4 Discussion

An automated CAD method is proposed in this study which focuses on diagnosing pediatric pneumonia on Chest X-ray dataset. The collected Pneumonia images are at first pre-processed and augmented. Then the images are fed to the deep CNN model which acts as a feature extractor and also as a classifier. This research uses pre-trained ChexNet model which is modified using fine-tuning.

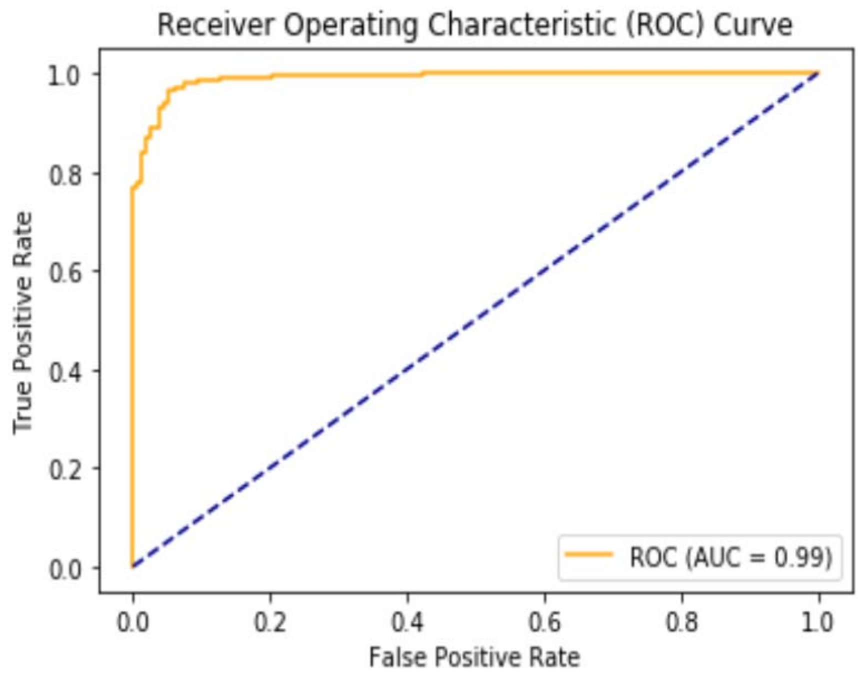

Fig. 6 ROC Curve of proposed final model.

The proposed CNN model outperforms VGG16, ResNet, DenseNet121, InceptionV3 and Xception, pre-trained fine tuned VGG19, Prateek et al., 2020, Liang et al., 2019 model achieving 92.6% test accuracy. PCA, as a feature reduction method is applied on the CNN features which are then fed to the LR classifier. Thus, the final model constructed by combining CNN, PCA and LR techniques, achieves the best classification results of about 96.1% on average which outperforms Stephen et al. (2019), and Saraiva et al. (2019) models.

The result of proposed CNN and the Final Model is compared with different existing models and proposed models for Accuracy and AUC values. The performance of the model at each step is portrayed in the result section.

Fig. 6 shows the Receiver Operating Characteristics (ROC) Curve of the final model. The area of ROC (AUC) obtained by the model is 99%.

CheXNet is used as a backbone of the proposed CNN model used in this work. CheXNet shows an AUC value of 0.768 for pneumonia classification. In Table 7, a relative comparison of AUC of the proposed final model with other models is shown.

Table 7 Comparison of different method's AUC.

Method	**AUC**
InseptionV3	0.655
CheXNet	0.768
DenseNet121	0.769
VGG16	0.840
Prateek et al. (2020)	0.911
Xception	0.930
Liang et al. (2019)	0.953
Saraiva et al. (2019)	0.98
Proposed Final Model	**0.994**

The comparison of Table 7 proves that the proposed final model is significant than other models including CheXNet. So, it can be said that the model is best in terms of accuracy and AUC than the others. Thus, the model can become a very helpful tool for the diagnosis of pediatric pneumonia.

Acknowledgment

The authors are grateful to the participants who contributed to this research.

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