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AI ENABLED PNEUMONIA DETECTION AND DIAGNOSIS BASED ON THE CONCATENATION APPROACH: A FRAMEWORK FOR HEALTHCARE SUSTAINABILITY

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Early detection and diagnosis of pneumonia play a significant role in saving human life. However, detection of pneumonia from chest X-ray images with the help of radiologists is a time-consuming task. Thus, the development of an appropriate artificial intelligence (AI) enabled model for the precise detection of pneumonia becomes an important research topic. In this aspect, we develop an automated transfer learning-based pneumonia detection framework using a feature concatenation approach. The proposed approach uses the DenseNet pre-trained network and concatenates the features extracted from several dense blocks of DenseNet in order to obtain the dense multiscale information from the chest X-ray images. This feature concatenation process helps in improving the classification accuracy of the proposed framework and simplifies the pneumonia detection process. The proposed work achieves accuracy, sensitivity, specificity, and precision of 98.60%, 97.03%, 99.14%, and 97.51%, respectively, on the chest X-ray pneumonia dataset which are superior results to the existing deep learning-based pneumonia frameworks. It is concluded that the proposed AI-enabled pneumonia detection framework has the prospective to be considered as a computer-aided diagnosis support system for the early diagnosis of pneumonia.

Keywords: artificial intelligence, healthcare, medical imaging, pneumonia detection, transfer learning, sustainability.

1. Introduction

In the present environment, various diseases are spreading in society every day due to contamination. This can result in a serious threat to human health. Pneumonia is considered one of the most severe diseases that are induced by different bacteria, viruses, and fungi (Stephen *et al.*, 2019). Anyone can be affected by this highly infectious disease including young or even healthy people. It can be more hazardous for infants, people having impaired immune responses, and people who suffered from prolonged diseases like asthma. However, pneumonia can be cured if it is detected and diagnosed early (Kowal *et al.*, 2021).

Generally, medical experts perform chest X-ray (CXR) image analysis for diagnosing the pneumonia disease. However, medical experts prefer X-ray imaging over other well-known imaging modalities used for healthcare, such as computed tomography (CT) and magnetic resonance imaging (MRI), because it is simple and cost-effective. The problem is that enough

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radiologists are needed to analyze chest X-ray images (Liang and Zheng, 2020a). It is observed that there is a scarcity of medical experts in many countries. In several situations, due to the scarcity of medical experts, any delay in disease diagnosis or in the treatment procedure of pneumonia leads to critical situations. Furthermore, the chest X-ray images have low resolution compared with the MRI and CT images, which makes pneumonia interpretation difficult and creates problems for medical experts in giving further recommendations (Siddiqi, 2019; Zhang *et al*., 2020). Therefore, a computer-assisted diagnosis support system is required for medical experts that will help in recognizing and extracting patterns. The advancements in an automatic pneumonia detection framework can act as a standby for radiologist-based diagnosis.

Recently, many researchers have recommended artificial intelligence (AI) based algorithms to provide solutions for the detection and classification of medical data. Machine learning also emerges as one of the sustainable solutions for the detection and diagnosis of pneumonia (Toğaçar *et al*., 2020; Muhammad *et al*., 2021). Usually, machine learning approaches require proficient image features as the input. Alternatively, deep learning models are capable enough to acquire the best image features for a particular task during the training stage (Kundu *et al*., 2021; Rahman *et al*., 2020a). Nowadays, there is remarkable success achieved by the deep learning frameworks for medical image processing tasks. Specifically, deep learning models, e.g., convolutional neural networks (CNNs), are extensively applied for the automatic identification of pneumonia and outperform other conventional approaches.

However, deep learning models achieve superior performance with high accuracy levels only when they are trained using a huge amount of labeled images. It is expensive as well as tedious to find a large amount of labeled medical images (Jain *et al*., 2020; Yang and Zhao, 2020). Further, more computational power is required to train the deep learning models from scratch. To overcome these issues, transfer learning models can be used that are already trained on a huge dataset for a specific task. The network parameters of the trained model are reused for another task (Chouhan *et al*., 2020). Thus, it will help to deal with situations where a limited amount of medical data is available. The models improve themselves based on the learning from a large dataset so that they are capable of recognizing images or classifying objects within the images (Ashok and Gopikrishnan, 2023; Cichosz, 2023).

Transfer learning is actually a deep learning strategy that empowers models for fast and accurate training by extracting reasonably valuable spatial features at the commencement of training learned from a large dataset. In transfer learning, the large dataset used for training the model is called the source dataset whereas the small dataset is called the target dataset. Usually, transfer learning techniques can be accomplished using pre-trained networks, e.g., VGGNet, GoogLeNet, AlexNet, and ResNet.

However, the pretrained network extracts the low-level features, e.g., texture, color, and edges using the top layers. Similarly, the bottom layers of the pretrained network extract the high-level features for example objects and contours. It is observed from the literature study that pre-trained networks generally use bottom layers for the extraction of high-level features for medical image classification tasks since these features are dissimilar from a normal image to a medical image. Instead of using only bottom layers for feature extraction, different layers of the pre-trained model should extract features. The extracted features should be concatenated to produce results in the form of multi-level information from input medical images. This may improve the feature capability of the image classification framework.

Consequently, in this work, we have proposed a transfer learning based pneumonia detection framework using chest X-rays based on the feature concatenation approach. We use the pretrained network DenseNet and concatenate the features extracted from several dense blocks of DenseNet to acquire the dense multiscale information from CXR images. This framework has been assessed using the Kaggle chest X-ray pneumonia dataset. The major contributions of the proposed transfer learning based pneumonia detection framework are as follows:

- Develops a proficient transfer learning framework based on the feature concatenation technique to automatically detect pneumonia with the help of CXR images.
- Produces dense multiscale information from chest X-ray images by means of a pretrained DenseNet network.
- Compares the proposed AI-enabled transfer learning-based pneumonia detection framework with contemporary AI-based pneumonia detection frameworks with respect to accuracy, sensitivity, specificity, AUC, and precision.

The paper is structured as follows: Section 2 describes the related deep learning-enabled work done for the diagnosis of pneumonia. Section 3 illustrates various methods and materials used for the proposed framework. This section explains the dataset, a summary of the pretrained DenseNet model, our proposed detection framework, and the evaluation metrics used for the assessment of the detection framework. Section 4 includes all the experimental results and related discussions. Section 5 concludes the article.

2. Related works

Currently, many researchers are emphasizing their research on biomedical problems like brain tumor detection, pneumonia detection, and brain hemorrhage diagnosis with the help of AI. Moreover, CNNs are a popular deep learning model utilized extensively for healthcare applications, particularly for medical image detection and classification tasks (El-Douh *et al*., 2022; Casalino *et al*., 2023; Rak *et al*., 2023). Particularly, most of the researchers have utilized deep learning approaches for automatic pneumonia detection tasks.

Jaiswal *et al*. (2019) proposed an efficient deep learning technique to find and localize pneumonia in CXR images. Here a DNN model is used that will include both local as well as global properties based on pixel-wise segmentation. Li *et al*. (2020) introduced a competent multi-resolution CNN-based framework to detect the lung nodule. Here, the authors found symptoms from several patches and used the fusion method for the classification task. This approach detected 99% of lung nodules effectively on the JSRT dataset.

Pasa *et al*. (2019) have proposed a faster and more efficient CNN-based framework for tuberculosis diagnosis. In addition, visualization methods, e.g., saliency maps and gradCAMs, were tested for tuberculosis. Sirazitdinov *et al*. (2019) proposed an automated approach by combining two CNNs, e.g., RetinaNet and Mask R-CNN, to detect and localize pneumonia. This approach produced outstanding results on a huge dataset comprising 26,684 chest images.

Souza *et al*. (2019) developed a novel approach that can automatically segment the lung portions with dense abnormalities called opacities. Usually, the opacities present in the lung region will create a challenge for the segmentation task. This proposed approach overcomes the problem that arises due to pulmonary abnormalities and can able to reconstruct the missing lung regions. Taylor *et al*. (2018) presented a deep convolutional neural network (DCNN) to train and test a CXR image dataset containing pneumothorax. This approach successfully detects moderate and large pneumothorax present in X-ray images. It can provide effective clinical alerts which can reduce the time required for treatment.

Further, Behzadi-Khormouji *et al*. (2020) also established a transfer learning-based approach to overcome the effect that arises due to opacities. They used the DCNN framework to detect consolidations present in the chest X-ray. This approach achieved a consolidation detection accuracy of 94.67%. Hashmi *et al*. (2020) further established a DCNN approach which will initially find the properties from chest X-rays and automatically detects the presence of pneumonia. They introduce the concept of a weighted classifier that has the capabilities to unite the weighted predictions achieved from various DCNN frameworks in an optimum way.

Woźniak *et al*. (2018) established a probabilistic neural network (PNN) based novel classification technique for lung carcinomas. Initially, the local maxima are found in the variance image and there, the location of the local maxima is used to find the contours of the probable lung nodules in the original image. Finally, a PNN is used as a classifier to differentiate between false nodules and true ones.

Ling and Cao (2019) introduced a novel support vector machine (SVM) based algorithm to detect severe viral pneumonia from CT images. They added the concept of linear discriminate analysis (LDA) in the SVM algorithm for the feature extraction task. The fusion of LDA and SVM makes the proposed method more efficient that provides more accurate detection results. Chowdhury *et al*. (2020) examine the effectiveness of artificial intelligence for both fast and precise COVID-19 detection from CXR images by using a pretrained DCNN. A public dataset containing 3487 CXR images was used to prove the performance of the proposed DCNN model. This technique performs classification between (a) normal class and COVID-19, (b) normal class, viral pneumonia, and COVID-19.

Khan *et al*. (2021) presented a comprehensive review of various intelligent pneumonia identification systems. Further, they presented a detailed exploration of the practicality, effectiveness, and computational complexity of the recent pneumonia identification frameworks. This comparative analysis will help the medical experts to understand the available datasets and selection of the best framework from a real-time viewpoint. Yaseliani *et al*. (2022) introduce a hybrid DCNN methodology for the detection of pneumonia with three efficient classifiers including SVM, logistic regression (LR), and radial basis functions (RBFs). The proposed hybrid DCNN model produced 98.55% detection accuracy with the SVM-RBF-LR ensemble classifier.

Feng *et al*. (2022) proposed a condense attention-based CNN model named PCXRNet for the diagnosis of pneumonia. This model effectively utilizes the prospective inter and intra relations of feature maps using two steps such as condensation and the squeeze-excitation step. This model achived a detection accuracy of 94.619% on the ChestXRay2017 dataset. Dhere and Sivaswamy (2022) introduced an innovative multi-scale attention approach for the classification of a normal class, a COVID class, and a non-COVID class using CXR images. The proposed architecture initially classifies between the a normal class and the pneumonia class using DenseNet and later, it differentiates between the COVID class and the non-COVID class using the MARL architecture (Malla *et al*., 2023).

The conventional deep learning approaches utilized for the detection of COVID-19 pneumonia from CXR

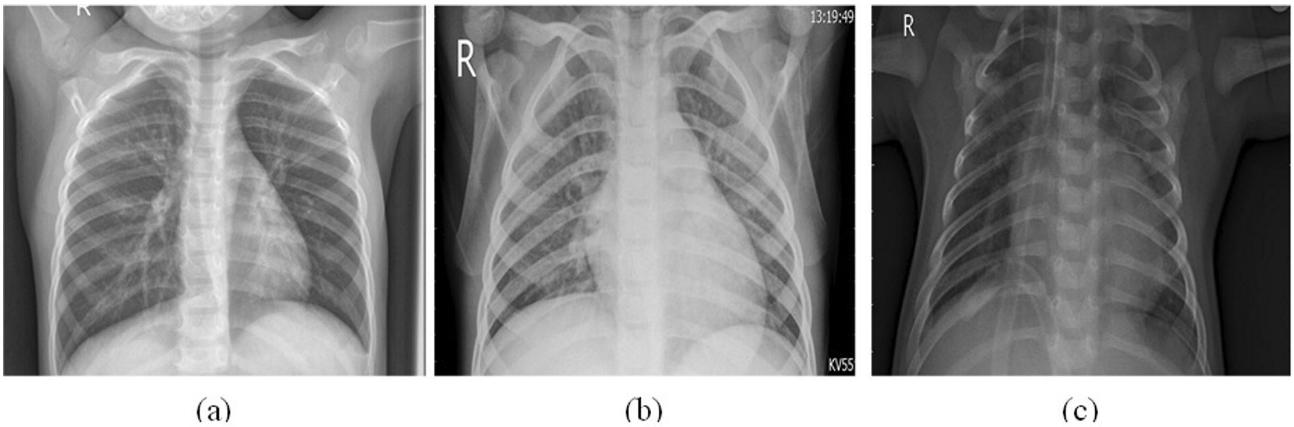

Fig. 1. Sample Kaggle chest X-ray pneumonia dataset: normal image (a), viral pneumonia image (b), bacterial pneumonia image (c).

images have deficiencies in interpreting the findings that limit their applications in clinical diagnostics. An innovative explainable DNN model was introduced by Zhang *et al*. (2022) and proposed to detect COVID-19 type of pneumonia accurately. To certify that the model may be trained on category samples, an additional encoder is inserted in this model following the encoder-decoder structure. Feng *et al*. (2021) developed one domain adaptation methodology for the automatic detection of pneumonia from a CXR image where the knowledge was transferred from ChestX-ray14 to the TTSH dataset. The proposed approach is different from the existing domain adaptation approach in a way that instead of performing the same task in both the source and target domain, it converts the information from a multiple label classification problem to a binary classification problem. This approach used two sub-networks which were trained in an end-to-end manner. In order to provide a timely and cost-effective pneumonia diagnosis, Hussain *et al*. (2023) proposed a deep ensemble strategy comprising three stages such as preprocessing, salient feature extraction, and classification. In addition, this method utilizes the abilities of VGG-16, DenseNet-201, and EfficientNet-B0 models for deep feature extraction from the images with an accuracy of 97%.

Fu *et al*. (2023) developed an efficient pneumonia detection framework which is capable of diagnosing pneumonia patients on an inadequate annotated CXR data. In this approach, the modified ResNet is used to construct a past knowledge-based active attention network that highlights the unique features and suppresses the inappropriate features. This approach efficiently classifies the pneumonia and healthy controls on a ChestXRay2017 with an accuracy of 97.63% and a sensitivity of 98.72%. The classification accuracy obtained by most CNN based models is still not convincing. Sheu *et al*. (2023) developed an eXplainable AI technique to implement an interpretable classification of pneumonia. This approach addressed the primary fact of pneumonia which affects people having low immunity. The key objective of this approach is to develop an interpretable pneumonia infection classification that delivers complete transparency analysis and transfer learning for high accuracy.

3. Material and methods

In this section, we will discuss the methodology and the dataset of chest X-ray for pneumonia diseases that have been used in this work. First, we will describe the details of the pneumonia dataset utilized for the research work. Then, we will illustrate the proposed transfer learning based methodology for pneumonia detection. Finally, we will discuss various performance indexes used for evaluating the performance of the proposed framework.

3.1. Dataset. We have used the Kaggle chest X-ray pneumonia dataset (Mooney, 2018) to assess the competence of the proposed AI-enabled transfer learning-based pneumonia detection framework. The dataset used in our experiment contains a total of 5247 CXR images. Further, the dataset is grouped into two classes such as the pneumonia class and the normal class. This dataset comprises 1341 normal images and 3906 pneumonia images. The pneumonia images are further classified as viral pneumonia (1345 images) and bacterial pneumonia (2561 images). However, we have combined both viral pneumonia and bacterial pneumonia as pneumonia classes to perform the binary classification among a normal class and a pneumonia class. This indicates that 25.5% of the total images are used for the normal class whereas 74.5% of images are used for the pneumonia class. In addition, the dataset utilized for the experiment is partitioned into a training and a test set where 70% of the total data are employed for training and validation of the model through cross-validation, while 30% of the total data are reserved exclusively for testing. This ensures that the test seth is disjoint from training/validation data and avoids any potential data leakage. Sample images of the Kaggle pneumonia dataset used for the experiment are shown in Fig. 1.

3.2. Data preprocessing and augmentation. Normally, raw CXR data are not in a format that can be directly used and may contain noise and missing values. These data cannot be directly provided as input to the deep learning model. The input data should be cleaned and made appropriate for the deep learning model so that the competency and accuracy of the model can be increased. During data preprocessing, input images from the dataset are processed through a preprocessing pipeline that includes image resizing, normalization, contrast adjustments, and augmentation to enhance the clarity of the image. The resizing ensured that all images had a uniform resolution of 224×224 pixels, and normalization mapped pixel values to the range $[0, 1]$. In our research, the CXR images are resized to 224×224 to be appropriate for the input of the DenseNet model. Further, all resized X-ray images are normalized between 0 and 1 agreeing to pretrained network standards. Data augmentation is a technique that can mitigate the absence of a large dataset by increasing the size of the training sample using a set of operations. In this experiment, the data augmentation schemes for example rotation, scaling, and translation are used to produce new training images. Specifically, the data augmentation was performed using operations: rotation (±15 degrees), scaling (10% up or down), and translation (5% horizontal/vertical shift). This helps in improving the performance metric scores of the proposed AI-enabled transfer learning-based pneumonia detection framework. The results of the data augmentation method on the pneumonia dataset are demonstrated in Fig. 2.

3.3. Network training. The input CXR images of the network are resized into 224×224 pixels. We use the ReLU activation function at each hidden layer of the network. To avoid the overfitting issues of the network, we set the dropout ratio to 0.2. We apply the dropout layers immediately before the feature concatenation stage, as illustrated in Fig. 4. We apply the Adam optimization algorithm for the optimization of the training process. Further, we adjust the batch size to 100, the epochs to 30, and the learning rate to 0.001. We employ 70% of the total data for the training of the model while 30% of the total data are employed for the testing and validation of the model. We use the cross-entropy loss function to resolve the multi-class classification task of our research work. We employ the SoftMax activation function at the last fully connected layer for the classification task.

3.4. Densely connected-convolutional network (DenseNet). DenseNet is a deep learning pretrained network used for the improvement of the depth of deep convolutional neural networks (DCNNs). However, it uses shorter connections between the layers to make the deep learning model more efficient (Huang *et al*., 2017). The evolution of DenseNet overcomes the vanishing gradient problems that arise in the case of traditional CNNs that use more layers. In the case of the DCNN, as the distance among the input and output layers is too long, the information about the inputs vanishes over time before reaching the destination (Wang *et al*., 2019). In the case of DenseNet, each layer is connected to its succeeding layers to transfer full information among different layers of the network. Each layer of DenseNet gets the input from the prior layers and forwards its own feature maps to the succeeding layers in order to achieve the feed-forward nature. DenseNet differs from ResNet in the way that its features are joined using concatenation, whereas ResNet's features are combined using summation. In addition to the convolutional and pooling layers, DenseNet further comprises two main blocks such as dense blocks and the transition layers.

In DenseNet, a transition layer is present between two dense blocks which perform operations such as batch normalization, convolution, and pooling operations. The basic organization of the DenseNet model is shown in Fig. 3. It is observed that the conventional CNN model with layers requires connections. The layers of DenseNet have inputs and comprise feature maps of its preceding layers. The feature maps of each layer of DenseNet are processed on to the succeeding layers. Hence, DenseNet provides a total of connections instead of connections provided by a conventional CNN.

Let the input image passed through the DenseNet be denoted by x_0. The transfer function of l-th layer of DenseNet is denoted by H_l. The output of the l-th layer can be defined as

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}]), \tag{1}$$

where $[x_0, x_1, \dots, x_{l-1}]$ represents the concatenations of feature maps such as x_0,$x_1, \dots, x_l$ generated in the previous layers 0,1, . . . , $l - 1$, respectively.

The nonlinear transfer function is defined as the combined function of three successive operations including batch normalization (BN), rectified linear unit (ReLU) and pooling $H_l(\cdot)$. The total number of feature maps available at the input of the l-th layer of DenseNet is $k_0 + k \cdot (l - 1)$. Here, k_0 represents the total number of channels and the transfer function H_l generates k feature maps at each layer. The parameter k is the growth rate of the DenseNet and a comparatively small growth rate is adequate for outstanding results on the datasets.

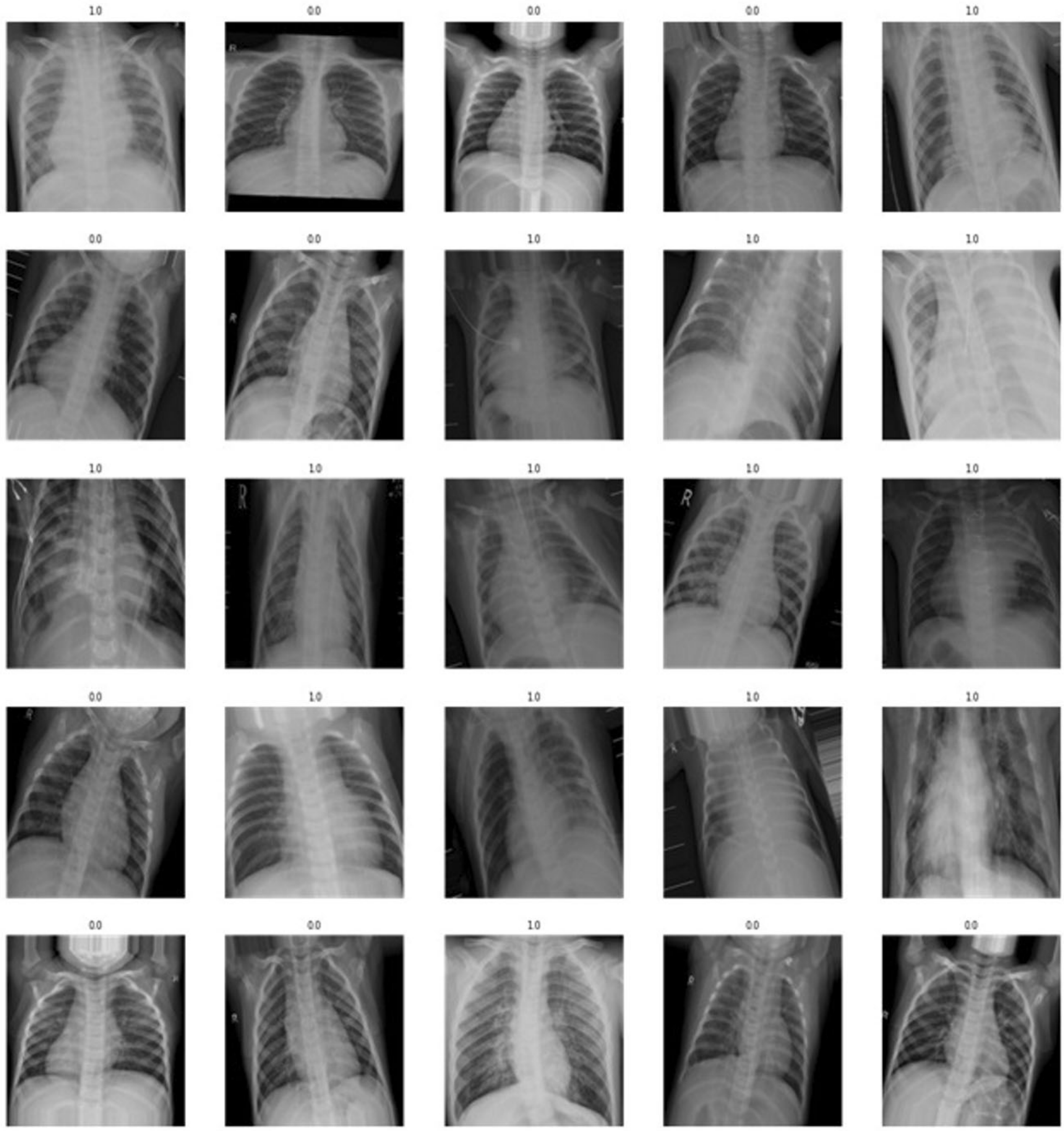

Fig. 2. Sample data augmentation results.

4. Proposed transfer learning based pneumonia detection framework

The primary aim of the proposed work is to introduce a proficient AI-enabled transfer learning-based pneumonia detection framework that can automatically find whether or not the patient has pneumonia at the very initial period using the chest X-rays. This approach will help in the treatment of the patient and subsequently prevent them from further impairment.

The block diagram of the proposed transfer learning-based pneumonia detection framework is illustrated in Fig. 4. This model employs the pretrained network 'DenseNet' and is based on the concatenation approach. We use DenseNet for the feature extraction from the CXR images. DenseNet consists of four dense blocks and numerous convolutional layers. However, the lower and upper dense blocks of the pretrained DenseNet are used for feature extraction. Once the feature extraction process from each dense block is complete, we employ the

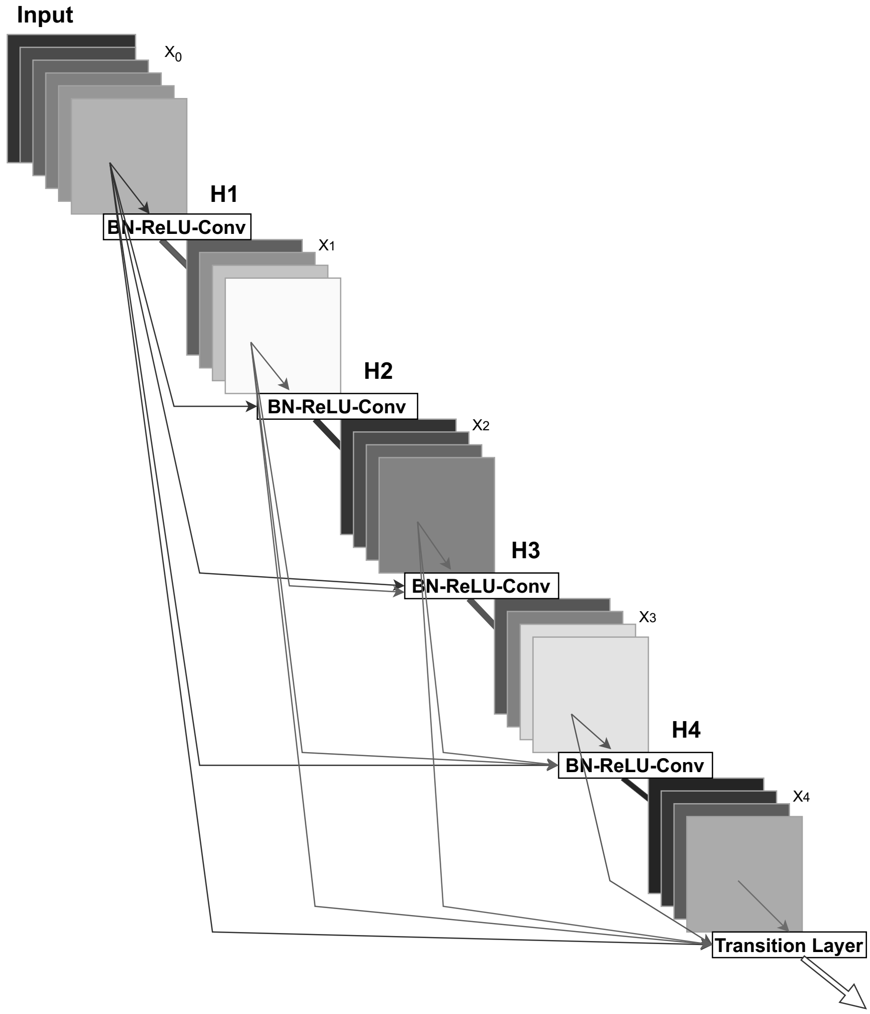

Fig. 3. Basic architecture of densely connected-convolutional network (DenseNet) (Chowdhury *et al*., 2020).

average pooling layer and a fully-connected layer for the feature concatenation purpose. Finally, the concatenated features are processed through the SoftMax classifier for the pneumonia detection and evaluation task. The main idea of introducing feature concatenation in DenseNet is that it produces dense multiscale information from chest X-rays. This idea assists in enhancing the classification accuracy of the proposed pneumonia detection framework that simplifies the pneumonia detection process.

The concatenation of the features generates comprehensive dense multiscale data from the CXR images for the purpose of pneumonia detection. The proposed pneumonia detection framework utilizes four interconnected dense blocks. These blocks were employed for both feature extraction and concatenation of features. The CXR images are used as input to DenseBlock-1 and then processed by the convolutional blocks. The convolutional blocks are commonly employed for detecting small features inside an image, while the pooling layer functions as a mechanism for reducing the size of the feature maps. Subsequently, the result of the pooling layer is utilized as the input to Dense Block-2, and this procedure is repeated for all four dense blocks. The proposed model utilizes convolution layers to detect edges, resulting in a feature map generated at each Dense Block. This feature map enhances the classification accuracy of our pneumonia detection model during training.

Our proposed pneumonia detection framework adopted the concept of transfer learning and fine tuning. Primarily, we import the pretrained weights from the ImageNet dataset which contains features precise to image classification. The utilization of the pretrained weights improves the image classification capabilities of our proposed pneumonia detection framework and reduces the processing time compared with the utilization of randomly initialized weights. Afterwards, to fine-tune the proposed pneumonia detection framework, we froze

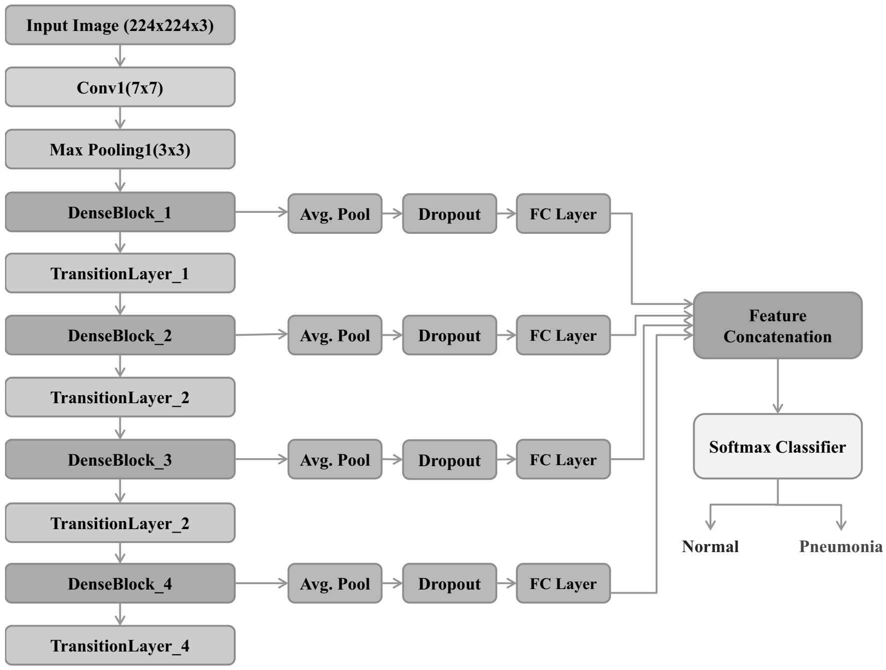

Fig. 4. Proposed pneumonia detection framework.

all the layers apart from the final layers and trained them using the Kaggle CXR pneumonia dataset. Thus, the framework avoids the initial layers from varying the weights and improves the training. After the training of the final layers using the Kaggle CXR pneumonia dataset, the whole network is unfrozen. Subsequently, the framework integrates weights from both the Kaggle CXR pneumonia dataset and the ImageNet dataset. The growth rate for all the relevant networks of the DenseNet architecture-based model is set to $k = 32$. Each convolution layer in the sequence follows the pattern of BN-ReLU-Conv as described in Fig. 3, except for the very first convolution layer which follows the pattern of Conv-BN-ReLU and has a filter size of 7×7.

CXR images may contain abnormalities in the shapes and patterns of large-scale textures, including structural distortion, organ enlargement, and opacity patches in the lung fields. A larger filter enables the model to see wider spatial objects, such as coarse shapes, edges, and general structures. At this stage, the convolutional layer allows a rough feature extractor which serves, using a lower dimension, to identify global patterns and passing information to perhaps deeper layers for more specific feature refining. The first convolutional layer employs a relatively large 7×7 filter size, which helps to detect abnormalities appearing on a large scale. This hierarchical method increases the model's capacity to recognize and evaluate important pathological characteristics.

ReLU utilized as the activation function in the proposed pneumonia framework for fully-connected layers is expressed as

$$f(x) = \max(0, x). \tag{2}$$

The ReLU activation function returns zero for the negative input and the same positive value for the positive input.

The SoftMax activation function is employed in the output layer due to its superior performance in multiclass classification tasks. It is defined as

$$P(y \mid x) = \frac{\exp(f_y)}{\sum \exp(f_c)}. \tag{3}$$

In this expression, y signifies the class and x signifies the input vector. Furthermore, f_c means the c-th element of the vector containing the class scores in the final fully connected layer. The SoftMax activation function selects the output class as the one with the highest probability value among all classes.

5. Experiment

We measure the proficiency of the proposed AI-enabled pneumonia detection framework using the Kaggle chest X-ray image dataset (Mooney, 2018). This section illustrates the evaluation metrics used for the performance assessment, network training, and the results obtained using our proposed approach and comparison with existing approaches.

5.1. Evaluation metrics. We assess the practicality of the proposed transfer learning based pneumonia detection

Table 1. Experimental results of the proposed transfer learning based pneumonia detection framework on the Kaggle chest X-ray dataset.

Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
98.60	97.03	99.14	97.51

framework using evaluation metrics for example accuracy, sensitivity, precision, specificity, area under curve (AUC) and F1 score. Accuracy signifies the percentage of accurately classified images out of all the images. It can be represented with the help of positives and negatives as

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \tag{4}$$

Sensitivity signifies the true positive rate,

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{5}$$

Specificity signifies the true negative rate,

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}. \tag{6}$$

Precision signifies the true positive measure,

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{7}$$

The F1 score signifies the mean of precision and sensitivity,

$$\text{F1-Score} = \frac{2\text{TP}}{2\text{TP} + \text{FN} + \text{FP}}. \tag{8}$$

The performance metrics defined in the above equations are epitomized by TP, TN, FP, and FN. A true positive (TP) signifies the output of the classification model that accurately predicts the positive class, i.e., the pneumonia images accurately predicted as the pneumonia category. Likewise, a true negative (TN) signifies the output of the classification model that accurately predicts the negative class i.e. normal images accurately predicted as a normal category. A false positive (FP) signifies the output of the classification model that inaccurately predicts the positive class, i.e., normal images inaccurately predicted as the pneumonia category. A false negative (FN) signifies the output of the classification model that inaccurately predicts the negative class, i.e., the number of pneumonia images inaccurately incorrectly predicted as the normal category (Bernardi *et al.*, 2014).

5.2. Results. Here, we discuss the experimental results achieved by the proposed transfer learning-based pneumonia detection framework on the pneumonia dataset. The concatenated feature extracted using our proposed approach helps in categorizing the normal and pneumonia classes in an effective manner. We have employed 202 normal images and 586 pneumonia images for testing our model. The sample output of the pneumonia detection framework is shown in Fig. 5. This figure illustrates the true and predicted image classes of our framework, for example, a normal image predicated as normal, a pneumonia image predicted as pneumonia and a normal image misclassified as pneumonia. The confusion matrix of our framework shown in Fig. 6 indicates that out of 202 normal images 6 samples are misclassified, whereas 5 samples are misclassified out of 586 pneumonia images. The receiver-operating characteristics (ROC) curve of our framework is shown in Fig. 7. Mainly, the ROC curve of the proposed AI-driven pneumonia detection framework was obtained by changing the threshold at the output layer of the model and is based on two parameters such as TPR and FPR. It corresponds to the median AUC value of the model and utilized to assess the diagnostic efficiency. It is observed that our framework achieves accuracy, sensitivity, specificity, and precision of 98.60%, 97.03%, 99.14%, and 97.51%, respectively, on the chest X-ray pneumonia dataset. The performance metric scores of the transfer learning based detection framework are shown in Table 1.

5.3. Discussion. We compare the proficiency of the proposed AI-enabled transfer learning-based pneumonia detection framework with some of the recent AI-based pneumonia detection frameworks developed by Liang and Zheng (2020b), Jain *et al.* (2020), and Rahman *et al.* (2020b), and Chouhan *et al.* (2020). We have taken performance measures, e.g., accuracy, sensitivity, precision, specificity, and AUC for the evaluation of the effectiveness of the proposed detection framework.

Liang and Zheng (2020b) proposed a transfer learning framework to identify pneumonia that utilizes the residual structure to deal with the overfitting issues of the DCNN model. Further, the authors introduce a dilated convolution in the proposed model to deal with the loss of feature space information issues that arise when the depth of the network increases. This framework achieves accuracy, sensitivity, precision, and AUC of 90.5%, 96.7%, 95.3%, and 89.1%, respectively, on the Kaggle dataset. Jain *et al.* (2020) developed a CNN-based pneumonia detection technique by using pretrained networks, e.g., VGG16, VGG19, ResNet50, and

Table 2. Performance scores in terms of accuracy (ACC), sensitivity (SS), specificity (SP), AUC and precision (PREC) of competing approaches.

Methods	Model used	No. of images used	ACC [%]	SS [%]	SP [%]	AUC [%]	PREC [%]
Liang and Zheng (2020b)	DCNN model	5856	90.5	96.7	–	95.3	89.1
Jain *et al.* (2020)	Various pretrained networks	5856	92.31	98.00	–	–	–
Rahman *et al.* (2020b)	Various pretrained networks	5247	98.00	99.00	97.00	98.00	97.00
Chouhan *et al.* (2020)	Ensemble approach	5232	96.39	99.62	–	99.34	93.28
Szepesi and Szilágyi (2022)	CNN with modified dropout	5856	97.20	97.30	–	98.20	97.40
Singh and Tripathi (2022)	Quaternion CNN	5856	93.75	–	–	–	–
Proposed method	Customized pre-trained DenseNet model	5247	98.60	97.03	99.14	99.48	97.51

Inception-v3, to classify pneumonia and non-pneumonia images. The authors have proposed six versions of the proposed model. They obtained accuracy and sensitivity of 92.31% and 98%, respectively. Rahman *et al*. (2020b) recommended an automatic pneumonia detection method based on several pretrained networks that can able to identify pneumonia and, further, categorize bacterial and viral pneumonia with maximum classification accuracy. The authors proposed four versions of the model using AlexNet, ResNet18, DenseNet201, and SqueezeNet respectively. It is observed that this approach achieves accuracy, sensitivity, precision, and AUC of 98%, 99%, 98%, and 97%, respectively, on the Kaggle CXR dataset.

Chouhan *et al*. (2020) introduced transfer learning-driven ensemble architecture for the identification of pneumonia. The authors proposed five versions of the model and, finally, ensemble the output of each model for higher classification accuracies. It is observed that this approach yields accuracy, sensitivity, precision, and AUC of 96.39%, 99.62%, 99.34%, and 93.28%, respectively. Szepesi and Szilágyi (2022) proposed a novel deep learning architecture by introducing the dropout concept in the convolutional part of the model instead of using it entirely in the fully connected part of the model. It is observed that this approach produces accuracy, sensitivity, precision, and AUC of 97.2%, 97.3%, 97.4%, and 98.2%, respectively. Singh and Tripathi (2022) introduced the concept of a quaternion residual network for the classification of pneumonia from CXR images. The main idea of the quaternion CNN is to consider the RGB channels of the color image as a single channel which, in turn, extracts better image features. It is observed that this approach produces accuracy and F1 score of 93.75% and 0.9405, respectively. This results in improving the classification accuracy.

The performance metrics scores of all the competing methods are illustrated in Table 2. It is found from the comparative analysis that the proposed pneumonia detection framework based on the concatenation approach outperforms other learning-based methods. All competing approaches are evaluated on the Kaggle CXR pneumonia dataset. Table 2 shows slight variations in the number of images used by different approaches. This discrepancy arises due to the exclusion of low-quality and irrelevant images during the data preprocessing stage. The outstanding performance of the proposed AI-enabled pneumonia detection framework is mainly due to the pretrained network DenseNet used in our proposed transfer learning-based pneumonia detection framework. The DenseNet constructs short paths from initial layers to subsequent layers by concatenation to relieve the vanishing gradient. The classification accuracy indicates the overall efficacy of the proposed model in classifying the actual positive and negative classes.

To understand the behavior of the proposed

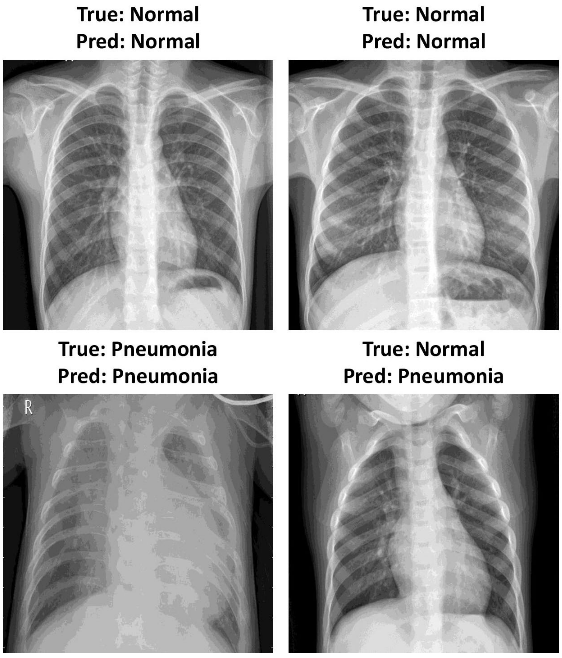

Fig. 5. Sample output of the proposed pneumonia detection framework.

pneumonia detection framework, we conduct the ablation study on the proposed framework to validate its robustness. In this process, we delete the convolutional layer from the framework one by one and measure the performance metric scores of the proposed framework. Further, we validate the effect of the deleted convolutional layer on the performance of the proposed method. The performance metric scores of the transfer learning-based detection framework after the ablation study are illustrated in Table 3. It has been observed from the performance metrics presented in Table 3 that the performance of the proposed method has been reduced by the application of the ablation study. Mainly, the model produced more false detections with the application of ablation. This indicates the proposed method is inclined to overfitting when the layers are deleted.

For the detection, classification, and diagnosis of pneumonia from CXR images, medical experts have utilized the conventional method based on human inspection. The human inspection method of detecting pneumonia is mainly based on the knowledge of radiologists regarding numerous image components. Since this approach is processed manually, it is difficult to handle large-scale pneumonia datasets and subsequently, it needs a lot of time. The AI-driven detection framework can process a large amount of data effectively in order to solve such issues. A major challenge of the pneumonia detection framework is to reduce the variance between high-level data recognized by a medical expert and low-level visual data captured by the X-ray. The main goal is to capture the best features by ignoring any nonsignificant features.

The proposed AI-driven pneumonia detection framework automatically extracts significant features using an ordered learning strategy. The initial layers of the proposed method extract basic features, for example, levels, edges, and shapes, whereas the final layers create intelligent interpretations of certain features. The low-level features of the CXR image, namely edges, contours, and texture information are extracted by the initial convolutional layers. Then the edges and contours identify the lung boundaries and rib structures. The texture information assists to distinguish infected from healthy lung regions. The intermediate dense blocks capture mid-level features like lung opacities as well granular/ reticular patterns. Lung opacities are useful to identify abnormal white patches, whereas granular and reticular patterns offer information regarding inflammation and infection. Finally, the last few dense blocks aggregate high-level features like disease-specific lesions and contextual information. Disease-specific lesions can help capture abnormalities associated with pneumonia. By contrast, contextual information helps distinguish pneumonia from normal and other lung diseases. This approach extracts the features from different dense blocks of DenseNet followed by concatenating the extracted features to get the dense multiscale information from CXR images. The combination of low-level and high-level features makes the proposed method an excellent choice for the detection and classification of pneumonia.

The proposed AI-driven pneumonia detection framework can be integrated in real real-world healthcare systems by considering the local context, for example, the clinical process, the patient's need, reliability, trust, safety, and constraints of medical, and ethical implications. The AI-driven healthcare system should be built with the consideration of the available technical infrastructure, data acquisition facilities, the equipment used, and the expertise of the personnel. The availability of multi-modal medical data, advanced technologies available on mobile, cutting-edge technologies like IoT, cloud computing, and data privacy enable the design of a powerful and safe AI-driven healthcare system. The development of reliable AI can minimize the gap between the deployment and integration of AI systems in real-world medical practices and subsequently, provides benefits in real-world applications.

6. Conclusion

This research work implements a transfer learning pneumonia detection framework that uses the DenseNet pretrained network based on a concatenation approach

Table 3. Performance scores of the proposed transfer learning based pneumonia detection framework on the Kaggle chest X-ray dataset after the ablation study.

Ablation Process	ACC [%]	SS [%]	SP [%]	PREC [%]
Deletion of 1st Layer	97.96	95.54	98.80	96.50
Deletion of 2nd Layer	98.22	96.07	98.97	97.03
Deletion of 3rd Layer	97.58	95.12	98.79	96.53

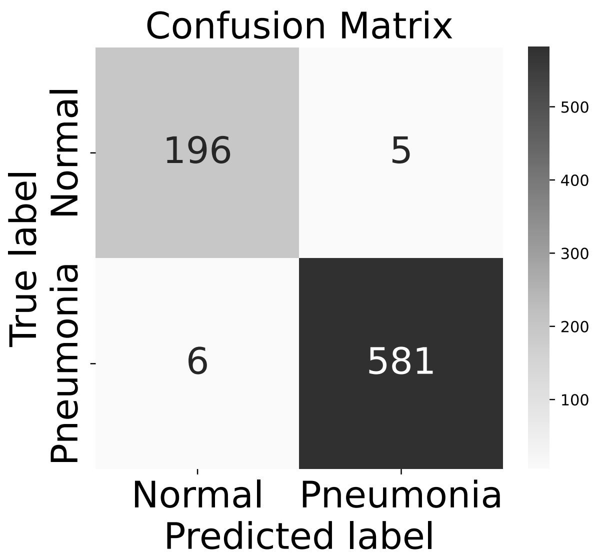

Fig. 6. Confusion matrix for classification of normal and pneumonia classes based on the proposed pneumonia detection framework.

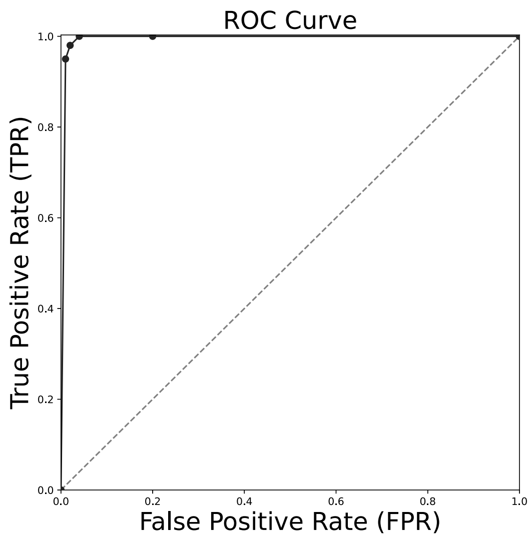

Fig. 7. ROC curve of the proposed pneumonia detection framework.

that can automatically identify whether or not the patient has pneumonia in the initial periods using the chest X-rays. This approach extracts the features from different dense blocks of DenseNet followed by concatenating the extracted features to get the dense multiscale information from CXR images. Thus, this approach can identify the most important latent features for a class. It strengthens the model's capacity to extrapolate to situations in real life where the distribution may change significantly.

A total of 5247 CXR images (1341 normal images and 3906 pneumonia images) are used for the evaluation of the proposed framework. The pneumonia detection framework acquires an accuracy of 98.60% in classifying the normal and pneumonia images and outperforms the prior state-of-the-art pneumonia detection models.

This proposed research work will be utilized as a decision support tool that will decrease the workload of medical experts and reduce the diagnosis error. Further, we will focus on distinguishing the severity of viral pneumonia automatically and detecting the more severe cases for early diagnosis in the future. Also, the proposed pneumonia detection framework can be employed for the identification of COVID-19 circumstances. The proposed approach will be suitable for multiple classifications (normal, pneumonia, and COVID-19) due to the feature concatenation method adopted by our approach. Further, during the data preprocessing stage in our approach, input images from the dataset are processed through a preprocessing pipeline where image resizing, shuffling, augmentation, and normalization are executed which, in turn, will reduce the inconsistencies in COVID-19 chest X-ray images.

Although this research work has achieved its objectives, it still has certain limitations. Therefore, the suggestions for future directions, progressions, and implementations of the proposed pneumonia detection framework are illustrated as follows. There is a requirement to develop methods for precisely identifying the areas of infection in CXR images. This can be combined with our proposed detection framework to help radiologists make more informed medical decisions. We can introduce the ensemble techniques in the proposed detection framework for a further improvement of classification accuracy. Specifically, we will ensemble three pretrained networks, for example, DenseNet, GoogLeNet, and ResNet to integrate the discriminative features that allow the model for superior predictions. The pneumonia detection framework can be seamlessly included in real-world healthcare systems by taking into account the clinical process, patient requirements, and ethical implications of medical practice.

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