A Proactive Approach in Detection of Pneumonia Disease using VGG16

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***Abstract*—** Pneumonia is a life-threatening disease caused by an infection or infection in the human lungs. Early diagnosis of pneumonia is an important part of effective treatment. The recent development of deep learning, which involves many layers to understand hierarchical data representation, has achieved the consequences of the state of many things, especially in the analysis and distribution of human diseases. Therefore, to improve the performance of lung cancer diagnosis, it is necessary to use automatic models based on deep learning models, which can detect images at high X-ray and facilitate lung diagnosis procedures for novices and patients. This paper develops a neural network (CNN) model for diagnosing lung disease using chest X-ray images. The proposed framework has two main stages: image preprocessing stage and feature extraction and image classification stage. The proposed CNN model provides high results with high performance, recall, F1 score, and accuracy of 98%, 98%, 97%, and 99.82%, respectively. According to the results, the proposed CNN model based on lung disease diagnosis achieved similar and accurate results and outperformed other previous deep learning models such as spare part (ResNet 50) and VGG16. It also goes beyond existing models recently mentioned in the literature. Therefore, the significant performance of CNN model-based lung diagnosis on all performance measures can provide better patient care and reduce mortality.

Keywords*— *deep CNN, ResNet 50, and VGG16 models

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I. INTRODUCTION

Pneumonia is a disease of the lung parenchyma caused by chemical and physical factors, the immune system, bacterial infection, and other inappropriate medications (1). According to the difference between non-infectious pneumonia, pneumonia can be divided into non-infectious and infectious pneumonia, divided into aspiration pneumonia and sentinel pneumonia, and pneumonia can be caused by viruses, bacteria, chlamydia, mycoplasma, etc. separable. Prompt diagnosis of pneumonia followed by appropriate treatment can help prevent deterioration of the patient's condition that could result in death [3].

Over the past few decades, many technologies have emerged that provide increasingly complex medical information, such as genomics and imaging. Chest X-ray is the preferred method for diagnosing pneumonia; However, these images are ambiguous and are sometimes not classified as benign or other conditions by radiologists, resulting in patients receiving the wrong medication and thus worsening their condition [5]. There is a need for an automatic and intelligent model to assist radiologists in the diagnosis of various lung diseases based on chest X-ray images [6].

Deep learning represents a subfield of machine learning that involves algorithms guided by brain models and operations [7]. Recently developed deep learning algorithms help measure, identify and classify patterns in medical images. Deep learning algorithms can learn features of data rather than self-generated features based on specific information. The most recently used deep learning model is neural networks (CNN). This model layer is dedicated to image processing and extraction of low-level features (such as edges) in the image. CNN layers can detect the body and location in the image with the help of filters. Unlike ordinary feedforward layers, CNN layers have a large number of parameters and use weight sharing techniques, thus reducing the computational cost. Therefore, this model can help doctors diagnose and classify certain diseases [8].

The main task of this project is to provide a deep learning method for the detection of lung diseases using chest x-ray images with equal performance of accuracy and complexity, while providing good results with fewer tools for doctors and radiologists. The purpose of the partnership is as follows:

(i) First, use the CNN model to detect lung disease from chest X-ray image based on the extraction and classification process

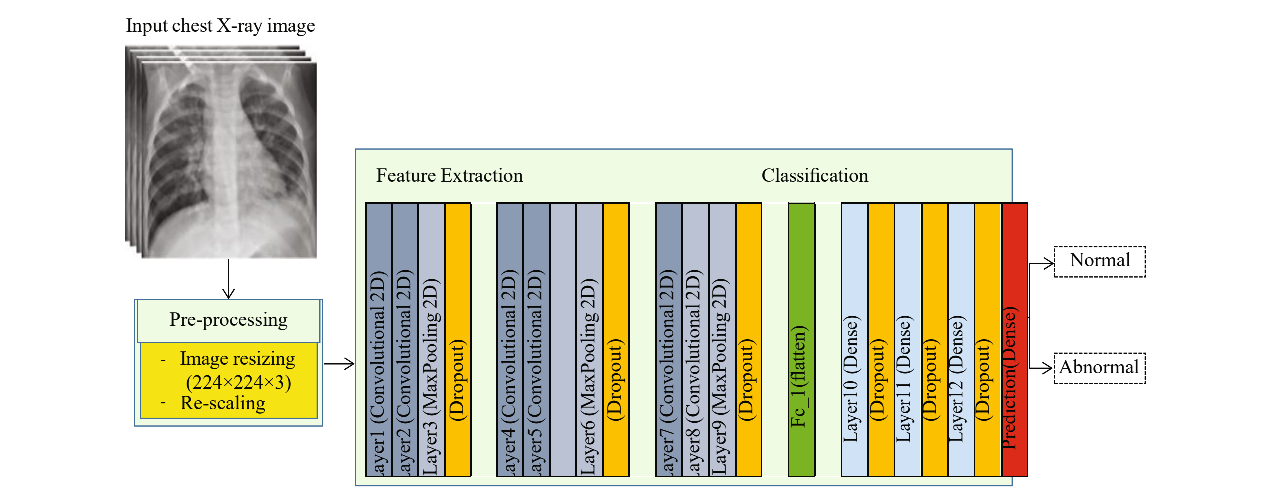

Figure 1: The proposed deep learning framework for detecting pneumonia disease.

(ii) Second, examine the processing success of CNN and other deep learning models in lung disease classification.

(iii) Finally, improve the model's ability to detect normal and abnormal images (lung disease).

The remainder of this paper is organized as follows: Section 2 provides a review of the work. Finally, Section 6 presents the conclusions of the pape

II. LITERATURE SURVEY

Ayan and änver [9] compared two CNN models (VGG16 and Xception) for lung disease diagnosis. In this model, adaptive learning and optimization are used in the learning process. The results show that the Vgg16 model outperforms the 0.85 is higher. VGG16 model. In addition, while the Xception model is more effective in diagnosing lung diseases than other models, the VGG16 model is more effective in diagnosing normal conditions. However, to achieve good results in the diagnosis of lung disease, these methods need to be combined (combined). Hashmi et al. [10] proposed a model for lung disease diagnosis in chest X-ray images. In this model, the data is first augmented, then predictions from deep learning models (Xception, Inception V3, ResNet 18, MobileNetV3, and DenseNet121) are combined and weighted elements are used to calculate the final prediction. This model outperforms other models with 98.43% accuracy. However, the standards used are quite complex; Therefore, it is necessary to provide a model that can estimate the weight of various models. Jain et al. [11] proposed a CNN model to classify chest X-ray images into pneumonia and non-pneumonia. These models differ in terms of parameters, hyperparameters, and convolution techniques used. The first and second models have three convolutional layers and provide 85.26% and 92.31% respectively, while the other models are pre-trained models (VGG16, VGG19) providing 87.28% and 92.31%, 88.46%, 70.99% respectively. , Inception V3 and ResNet 50). % and 77.56%. This practice model focuses on repeated measurements, such as auditors' performance, to minimize the number of negatives. The second model has the best recovery rate at 98%. However, these models need to fine-tune each parameter and hyperparameter to improve classification accuracy. Al Mamluk et al. [12] proposed seven models to detect and classify lung diseases from chest X-ray images; these models are random forest, decision tree, K nearest neighbors, adaptive, gradient boosting, XGBboost and CNN.

TABlE 1: The parameters of the CNN model layers.

Layers (types)	Shape_output	Parameters
layer1 (convolutional 2D)	None, “224, 224, 64”	1792
layer2 (convolutional 2D)	None, “224, 224, 64”	36928
layer3 (max pooling 2D)	None, “112, 112, 64”	0
(Dropout)	None, “112, 112, 64”	0
layer4 (convolutional 2D)	None, “112, 112, 128”	73856
layer5 (convolutional 2D)	None, “112, 112, 128”	147584
layer6 (max pooling 2D)	None, “56, 56, 128”	0
(Dropout)	None, “56, 56, 128”	0
layer7 (convolutional 2D)	None, “56, 56, 256”	295168
layer8 (convolutional 2D)	None, “56, 56, 256”	590080
layer9 (max pooling 2D)	None, “28, 28, 256”	0
(Dropout)	None, “28, 28, 256”	0
(Flatten)	None, “200704”	0
layer10 (dense)	None, “512”	102760960
(Dropout)	None, “512”	0
layer11 (dense)	None, “128”	65664
(Dropout)	None, “128”	0
layer12 (dense)	None, “64”	8256
(Dropout)	None, “64”	0
(Dense)	None, “2”	130

Total of parameters: 103,980,418 Trainable parameters: 103,980,418 Nontrainable parameters: 0

Specifically, all these models were compared with their f-scores and accuracy scores. The CNN model slightly outperforms other machine learning models, achieving an accuracy of 98.46%. Surprisingly, the random forest model achieved very good results with 97.61% accuracy. However, in order for these models to provide better results, large data sets must be created for training and testing purposes. Wu et al. [13] proposed to improve median filter based on CNN model using random forest matching. In this model, an adaptive median filter is first used to remove noise from the chest X-ray image to facilitate identification; Then, a dropout-based CNN architecture was designed to extract highly activated features from each image. Finally, a random forest based on the GridSearchCV cluster is adopted as a distribution for deep processing in the CNN model. This model not only prevents overfitting in training data but also improves the accuracy of image classification. The accuracy score is 96.9% for the 64×64×3 image size and 93.8% for the 224×224×3 image size. According to the accuracy achieved, accuracy, recall and F1 score are 90%, 95% and 97.7%, respectively. However, the model needs to improve the performance of the CNN model so that it can run more efficiently and without the need for additional preprocessing. Chou-han et al. [14] proposed a deep learning method based on transformational learning to diagnose lung disease. In this framework, the chest X-ray image is first brought to 224×224×3 size and enhanced (random horizontal tilt, random change of cropping size and different density) are used. Then, features are extracted from the images using various models (AlexNet, Inception V3, DenseNet121, ResNet 18 and GoogLeNet) before training on the data and transferred to classes that learn to predict. Finally, a combination model is obtained using the pre-trained model and passed through a single model. The recall and accuracy results are 99.62% and 96.4%, respectively. However, the effectiveness of this framework needs to be further increased by increasing the data size or using hand tools. Zhang et al. [15] proposed a CNN-based lung disease diagnosis model. This model first uses dynamic histogram equalization technology to improve the contrast of chest X-ray images; Then, a VGG-based CNN model was designed for feature extraction and classification. The model was able to detect abnormalities and chest X-ray images with 94.41% accuracy and 96.07% accuracy. However, this model needs to be investigated for a more accurate classification for lung disease diagnosis. Manickam et al. [16] used U-Net as a segmentation architecture and used pre-trained models (Inception V3, ResNet 50, and Inception-ResNet V2) to pre-process input images of chest X-ray to determine the presence of lung cancer. The ResNet 50 model outperformed other models with 96.78% recall, 88.97% precision, 92.71% F1 score, and 93.06%

TABLE I
Literature Survey

S.No	Title	Author	Methodology	Key Findings
1	Pneumonia Detection Using Convolutional Neural Networks (CNNs)	V. Sirish Kaushik, Anand Nayyar, Gaurav Kataria and Rachna Jain	Convolutional neural networks (CNNs) · Pneumonia detection · ReLU · Max-pooling · Forward and backward propagation.	The validation accuracy, recall and F1 score of CNN classifier model 3 with three convolutional layers are 92.31%, 98% and 94%, respectively, which are quite high compared to other models that were trained.
2	Neural architecture search for pneumonia diagnosis from chest X-rays	AbhibhaGupta1,4, Parth Sheth2,4 & Pengtao Xie3	Learning by Teaching (LBT) framework to perform diferential architecture search to discover the most efective neural architecture for	This method yields an area under ROC curve (AUC) of 97.6% for pneumonia detection, which improves upon previous NAS methods by 5.1% (absolute).

			detecting pneumonia from chest X-ray images. We also experiment with other methods for neural architecture search such as DARTS7 and PC-DARTS8.	
3	Pneumonia Detection Using CNN based Feature Extraction	Dimpy Varshni, Kartik Thakral, Lucky Agarwal, Rahul Nijhawan, , Ankush Mittal	Pneumonia detection system using the 'Densely Connected Convolutional Neural Network' (DenseNet-169) is described in Figure 2. The architecture of the proposed model has been divided into three different stages - the preprocessing stage, the featureextraction stage and the classification stage.	CNN models along with distinct classifiers and then on the basis of statistical results selected DenseNet-169 for the feature extraction stage and SVM for the classification stage. We also showed that performing hyperparameter optimization in the classification stage ameliorated the model performance.
4	PNEUMONIA DETECTION ON CHEST X-RAY USING RADIOMIC FEATURES AND CONTRASTIVE LEARNING	Yan Han1, Chongyan Chen2, Ahmed Tewfik1, Ying Ding2,* , Yifan Peng3,	radiomics; medical imaging; CNN; chest X-ray; neural networks; interpretability	framework by combining radiomic features and contrastive learning to detect pneumonia from chest X-ray. Experimental results showed that our proposed models could achieve superior performance to baselines
5	Pneumonia detection in chest X-ray images using an ensemble of deep learning models	Rohit KunduID1 , Ritacheta DasID2 , Zong Woo GeemID3 *, Gi-Tae HanID3 , Ram SarkarID	an ensemble framework of three classifiers (Fig 2), GoogLeNet [34], ResNet-18 [35], and DenseNet-121 [36], using a weighted average ensemble scheme wherein the weights allocated to the classifiers are generated using a novel scheme, as explained in detail in the following sections	This method achieved accuracy rates of 98.81% and 86.85% and sensitivity rates of 98.80% and 87.02% on the Kermany and RSNA datasets, respectively.
6	A Review on Detection of Pneumonia in Chest	Daniel Joseph Alapat1 , Malavika	Pneumonia; Convolution Neural Networks; Mass Chest X-ray; Chest X-	The combination of the 5 models had remarkable results of ROC AUC of

	X-ray Images Using Neural Networks	Venu Menon1 , Sharmila Ashok2	ray14; Diagnosis, Computer-Assisted; Deep Learning	0.9934 with testing accuracy of 96.39% and a high sensitivity of 99.62%.
7	Pneumonia Detection Using Deep Learning Based on Convolutional Neural Network	Luka Račić, Tomo Popović, Senior Member, IEEE, Stevan Čakić, Stevan Šandi	artificial intelligence; convolutional neural network; deep learning; image processing, machine learning; pneumonia detection	the 90% accuracy means that the prediction model could potentially be used as a decision support tool, but there is still much work to be done
8	Convolutional Neural Network Applied to X-Ray Medical Imagery for Pneumonia Identification	Denis Manolescu1,2 , Neil Buckley1 , and Emanuele Lindo Secco	This paper presents an experimental study focused on analyzing the structure and functionality of convolutional neural networks by building an operational model capable of identifying cases of pneumonia from X-ray scans	The CNN model is trained, validated and tested on a dataset of over 5000 images, and the final results show 99% precision and 98% accuracy, with a recall value of 98%.
9	Detection of Pneumonia Infection by Using Deep Learning on a Mobile Platform	Alhazmi Lamia 1 and Alassery Fawaz 2	the model can now be accessed by anyone, anywhere, via a mobile application. *e dataset of more than 5,000 real images was used to train an image classification model using Create ML, a tool with a graphical interface, and there was no need for specialized knowledge.	Using the existing data, it was possible to train several models with different configurations whose accuracies vary between ~78% and ~85%; we can conclude that the model's capabilities can be expanded if sufficient training data is available
10	Pneumonia Detection on Chest X-ray Images Using Ensemble of Deep Convolutional Neural Networks	Alhassan Mabrouk 1,* , Rebeca P. Díaz Redondo 2, Abdelghani Dahou 3, Mohamed Abd Elaziz 4,5,6and Mohammed Kayed 7	image processing; deep learning; medical image classification; ensemble deep learning; vision transformer	The proposed EL approach outperforms other existing state-of-the-art methods and obtains an accuracy of 93.91% and a F1-score of 93.88% on the testing phase.
11	Development of Pneumonia Disease Detection Model Based on Deep Learning Algorithm	Dalya S. Al-Dulaimi,1 Aseel Ghazi Mahmoud,2 Nadia Moqbel Hassan,3 Ahmed	. A convolutional neural network (CNN) model is developed in this paper for detecting pneumonia via utilizing the images of	The proposed CNN model provides high results of precision, recall, F1-score, and accuracy by 98%, 98%, 97%, and 99.82%, respectively.

		Alkhayyat , 4 and Sayf A. Majeed	chest X-rays. The proposed framework encompasses two main stages: the stage of image preprocessing and the stage of extracting features and image classification	
12	Detection of pneumonia infection in lungs from chest X-ray images using deep convolutional neural network and content-based image retrieval techniques	T. Rajasenbagam1 · S. Jeyanthi2 · J. Arun Pandian3	The performance of the proposed deep CNN was compared with state-of-the-art transfer learning techniques such as AlexNet, VGG16Net and InceptionNet. The comparison results show that the classifcation performance of the proposed Deep CNN model was greater than the other techniques.	. The classifcation accuracy of the proposed Deep CNN model was 99.34 percent in the unseen chest X-ray images
13	Detection of pneumonia using convolutional neural networks and deep learning	Patrik Szepesi a , La´ szlo´ Saila´ Gyi	The chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients, aged between one and five years, from Guangzhou Women and Children's Medical Center, Guangzhou, China.	Results achieved by our net-work 97.2% accuracy, 97.3% recall, 97.4% precision and AUC ¼ 0:982, and they are competitive with current state-of-the-art solution
14	PNEUMONIA DETECTION USING IMAGE PROCESSING AND DEEP LEARNING APPROACH	HEMALATHA INDUKURI, DASARI DEEPTHI PRABHASRI, CHELLUBOINA DEEPTHI.	In comparison to other applied models, the collected results demonstrated that the suggested CNN model-based pneumonia detection has the greatest precision, recall, F1 score, and with superior accuracy	the results will be more accurate (92%) and produce superior results, making the suggested system essential in the decision-making process.

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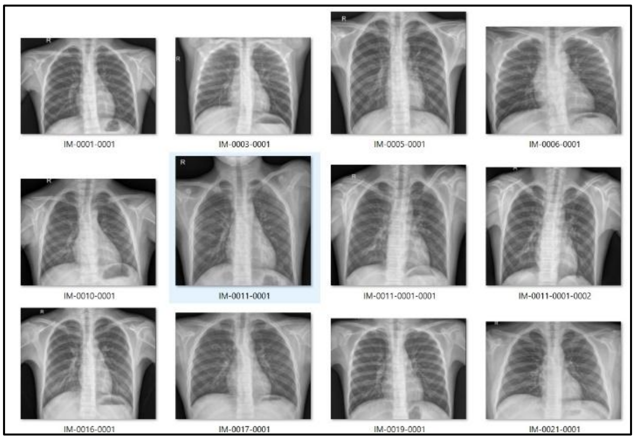
Most of these related studies are based on using pre-trained methods of neural networks or finding certain patterns with certain methods. In addition to the complexity of the features that the neural ne

TABLE 4: The obtained metrics of precision, recall, F1-score, and accuracy for VGG16 model.

Pneumonia classes	Precision	Recall	F1-score	No. of tested images
"Abnormal"	0.88	0.73	0.80	855
"Normal"	0.50	0.74	0.62	318
Accuracy			0.73	1173
Macroaverage	0.74	0.73	0.73	1173
Weighted average	0.73	0.73	0.71	1173

Figure 2: Examples of Normal Lungs

twork finds to perform the required tasks, the computational process also increases when the number of operations increases, but this does not mean that there is an improvement in accuracy. Additionally, using more than one layer will reduce the accuracy of the neural network due to the inability to detect features of the required complexity. Therefore, the main purpose of this study is to build a good deep CNN model of publicly available data and achieve its goal in order to achieve its goal. The main responsibility of this work is to use a deep CNN model on publicly available data to recognize pneumonia, striking a balance between accuracy and complexity.



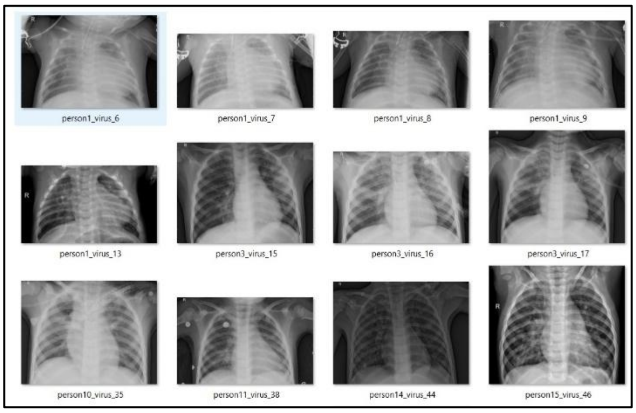


Figure 3 Examples of Pneumonic Lungs

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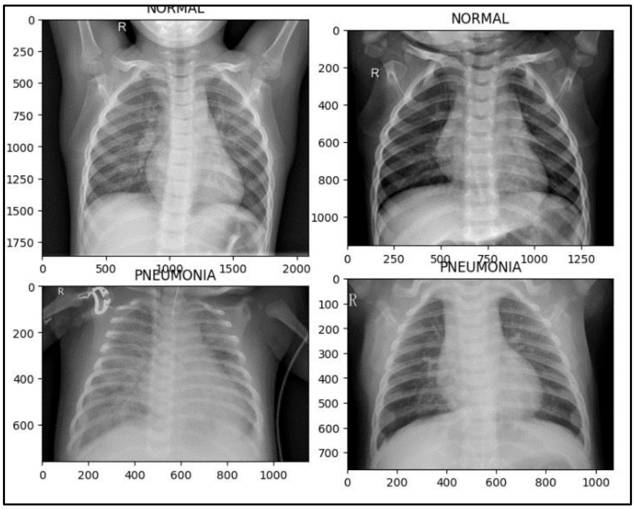


Figure 4 Examples of Chest X-Rays.

TABLE 2: The obtained metrics of precision, recall, F1-score, and accuracy for the proposed CNN model.

Pneumonia classes	Precision	Recall	F1-score	No. of tested images
"Abnormal"	0.98	0.96	0.99	855
"Normal"	0.98	0.97	0.98	318
Accuracy	—	—	0.99	1173
Macroaverage	0.99	0.98	0.97	1173
Weighted average	0.98	0.98	0.97	1173

TABLE 3: The obtained metrics of precision, recall, F1-score, and accuracy for ResNet 50 model.

Pneumonia classes	Precision	Recall	F1-score	No. of tested images
"Abnormal"	0.95	0.98	0.97	855
"Normal"	0.94	0.86	0.90	318
Accuracy	—	—	0.95	1173
Macroaverage	0.95	0.92	0.93	1173
Weighted average	0.95	0.95	0.95	1173

III. METHODOLOGY

Deep learning methods are developed and trained multiple times using multiple parameters to choose better hyperparameters and provide parallelism to models. In general, it has two main stages. In the first stage, there are a number of pre-processing steps, the image is converted to obtain an image size of 224×224×3, and then the pixel values of the image are converted to [0, 1] values. Feature extraction and image classification.

The proposed CNN model is used as an extraction and classification strategy to detect lung disease from chest X-ray images. Figure 1 shows the general structure of the

pneumonia diagnostic model. The model has three elements. The input process in the CNN model represents the first part (process) of the CNN model, which transfers the 224×224×3 chest x-ray image to the next part.

Feature extraction represents the second part of the CNN model and consists of three blocks, each containing a convolution layer, a maximum pooling layer, and an output layer. In the convolution layer, the input image is converted into matrix form. Convolution operation is used on the input matrix and the 3x3D feature kernel, and the result represents the feature map. This function reduces the size of the image, making it easier to work with.

All layers are based on rectified linear units (ReLU) for better performance. ReLU is a general function that is logical (changes the input to 0 if its value is less than 0) and produces a non-linear output.

The maximum pooling layer is then used to identify important features in the image and reduce the size and negative of the image, thus reducing the complexity of the match. A 2×2 dimensional max pooling layer is run on each map and measures its dimensions using the "MA" function, which is used to select the maximum value of the pixel from the hole image window. Dropout is added to the max pooling layer to prevent overfitting.

The output of the second part is then transferred to the third part, the proportion. There are several layers to this; The first color layer, which transforms the shape of the data into a one-dimensional vector, followed by three thick layers, each following the output process, and finally the thick layer with a sigmoid function used to classify the output images as normal or abnormal. Table 1 shows the number of parameters used in the CNN model for lung disease diagnosis.

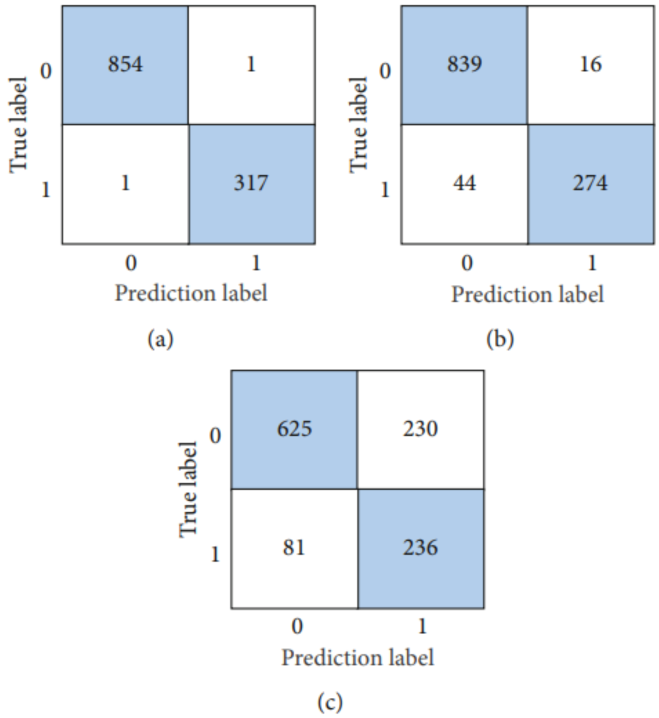


FIGURE 3: Confusion matrices: (a) proposed CNN model, (b) ResNet 50 model, and (c) VGG16 model.

IV. COMPUTATIONAL EXPERIMENTS

Python programming language is used to implement deep request CNN, ResNet 50 and VGG16 models. Google Colab is used as the GPU runtime during the training and validation phase. Each model was optimized for 100 periods with a batch size of 128. The NAdam optimizer was used to optimize the learning function with a learning rate of 0.001.

According to the pre-processing CNN model, VGG16 contains 16 layers (13 layers of layers and 3 thick layers) while ResNet 50 contains 50 layers (48 layers of layers, 1 layer of layers and 1 half of layers). VGG16 has about 134 million training parameters and ResNet 50 has about 23 million training parameters. The same image preprocessing step is used in pretraining models, while feature extraction and classification steps follow the pattern of each model.

4.1. Dataset Description. Our deep learning model for lung disease diagnosis was trained and tested on images from the chest x-ray dataset [17] containing 5880 samples, 80% (4707 samples) of which were used to illustrate this model, 20% (1173) of which were used to illustrate this model. It was used to train. Figure 2 shows examples of chest X-ray images where abnormal pneumonia shows an interstitial pattern in the lungs, abnormal pneumonia shows focal lobar consolidation, and normal images show Clear lungs without abnormal opacification. Positive ion field in X-rays.

4.2. Evaluation Metrics. The utilized performance metrics for identifying the best model are precision, recall, F1-score, and accuracy. In order to compute these metrics, True Negative "Tneg," True Positive "Tpos," False Negative

"Fneg," and False Positive "Fpos" are provided. The lower the Tneg and Tpos, the fewer classifiers' performance that capable of detecting normal and abnormal (pneumonia) images. The higher the Fpos and Fneg, the higher classifiers mistakes that misclassify pneumonia images as normal images and conversely. The specificity metric indicates the ability of classifiers to recognize the normal images; it is assigned by Tneg and Fpos as in

$$\text{Specificity} = \frac{T_{\text{neg}}}{(T_{\text{neg}} + F_{\text{pos}})}. \quad (1)$$

The precision metric works on measuring the real abnormal (pneumonia) image percentage from all predicted abnormal images, as in

$$\text{Precision} = \frac{T_{\text{pos}}}{(T_{\text{pos}} + F_{\text{pos}})}. \quad (2)$$

The recall metric (sensitivity) is a properly classified class from the model of classification, and the sensitivity with a high value will make the model more reliable and robust. This metric is associated with Tpos, as in

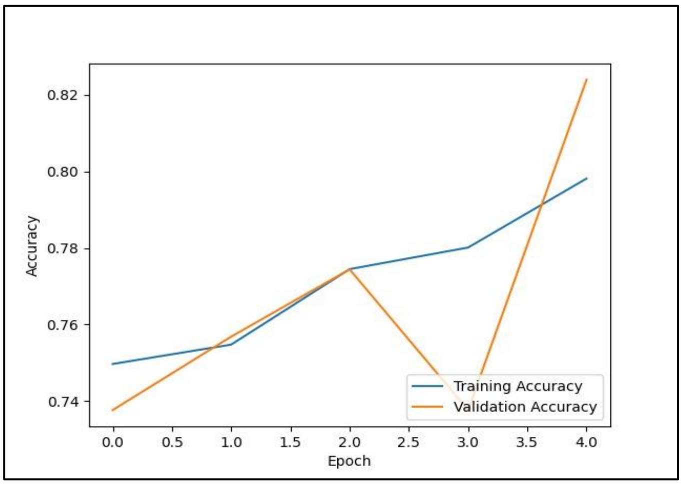
$$\text{Recall} = \frac{T_{\text{pos}}}{(T_{\text{pos}} + F_{\text{neg}})}. \quad (3)$$

The accuracy metric is utilized for measuring the classification models' performance, and in other words, represents the total classifier performance that is measured by

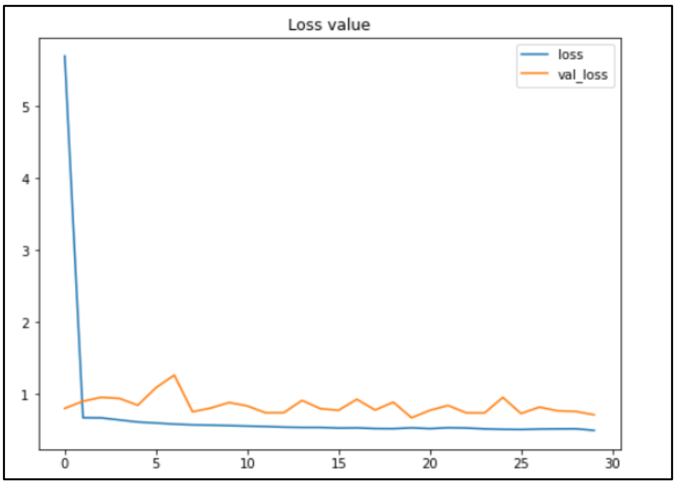
$$\text{Accuracy} = \frac{(T_{\text{neg}} + T_{\text{pos}})}{(T_{\text{neg}} + F_{\text{pos}} + T_{\text{pos}} + F_{\text{neg}})}. \quad (4)$$

And finally, F1-score indicates the classifiers' ability of classification via utilizing the combination of precision and recall metrics as a single evaluation metric of performance, as in

$$\text{F1} - \text{score} = \frac{2(Precision \times Accuracy)}{(Precision + Accuracy)}. \quad (5)$$



(a)



(b)

Figure 5: ResNet 50-based pneumonia disease recognition: (a) accuracy per epoch and (b) loss per epoch

V. RESULTS AND DISCUSSION

Tables 2-4 show the measurement results (precision, recall, F1 score, and accuracy) used by the CNN model, ResNet 50, and VGG16 model, respectively.

As shown in Table 2, the CNN model has the best precision, recall, F1 score, and accuracy of 98%, 98%, 97%, and 99.82%, respectively.

The accuracy, recall, F1 scores, and accuracy results for ResNet 50 models (shown in Table 3) are 95%, 95%, 95%, and 95.37%, respectively.

The accuracy, recall, F1 score, and accuracy of the VGG16 model (shown in Table 4) are 73%, 73%, 71%, and 73.40%, respectively.

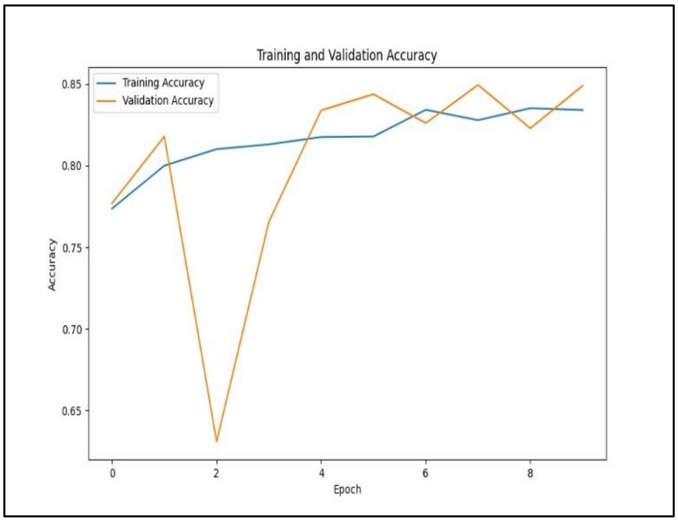
The confusion matrix provides an understanding of the error obtained from the distribution used. It is used to describe the performance of experimental images for which the ground truth is known. Figure 3 shows the confusion matrices of the CNN, ResNet 50, and VGG16 models.

Experiments were performed 100 times, 128 dimensions and with the "Nadam" optimizer. The environmental accuracy and environmental losses of the CNN, ResNet 50 and VGG16 models are shown in Figures 4-6, respectively.

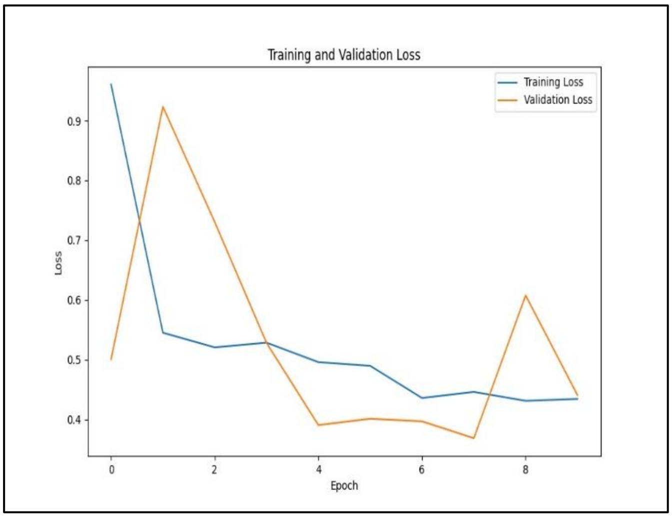
As shown in Figure 4, the training and validation accuracy and training and validation loss curves of the CNN model prepared for 100 epochs are 99.82%, 96.53%, 0.0110 and 0.2005, respectively.

The proposed model was evaluated by comparing it with the ResNet 50 and VGG16 models, as well as new models using chest X-ray images, as shown in Table 5.

As shown in Table 5, lung diagnosis based on CNN model achieved similar and accurate results, outperformed ResNet 50 and VGG16 models, and outperformed other short-term models.



(a)



(b)

Figure 6: VGG16-based pneumonia disease recognition: (a) accuracy per epoch and (b) loss per epoch.

VI. CONCLUSION

This article presents a deep learning model to detect pneumonia from chest X-ray images. The number of layers does not always improve accuracy, and increasing the network layer will have a negative effect. It is undoubtedly possible to find the number of layers that will provide the best accuracy during the construction of the CNN model.

The results show that based on lung disease diagnosis, the proposed CNN model has the best accuracy, recall, F1 score, and accuracy of 98%, 98%, 97%, and 99.82%, respectively, which indicates that this model is better than other applications. makes it possible to use more. . model in addition to the electrician's decision. The results support the idea that deep learning models can simplify the diagnostic process and improve the quality of treatment by improving the management of lung diseases. It has also been reported that the CNN model performs better than other models recently proposed in the literature. The model can be effectively used to diagnose other diseases such as pneumonia and COVID-19.

TABLE 5: A comparison between the proposed model and other models.

Ref.	Learning models	Precision	Recall	F1-score	Accuracy
[9]	Xception	86%	85%	87%	82%
	VGG16	91%	82%	90%	87%
[10]	Weighted classifier based pretrained models	—	—	98.63%	98.43%
[11]	Inception V3	86%	84%	78%	70.99%
	ResNet 50	92%	97%	84%	77.56%
	VGG16	93%	96%	90%	87.18%
	VGG19	94%	95%	91%	88.46%
[12]	CNN	—	—	98.95%	98.46%
[13]	CNN-random forest	90%	95%	97%	93.8%
[14]	Ensemble model	93.28%	99.62%	94.8%	96.39%
[15]	VGG-based CNN model	94.41%	—	—	96.07%
[16]	ResNet 50	88.97%	96.78%	92.71%	93.06%
—	ResNet 50	95%	95%	95%	95.37
—	VGG16	73%	73%	71%	73.40%
—	Proposed CNN model	98%	98%	97%	99.82%

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