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An Efficient Deep-learning Model to Diagnose Lung Diseases using X-Ray Images

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Abstract: The coronavirus 2019 (COVID-19) pandemic carrying on to seriously affect the health and well-being of the world-wide public. Effectively screening those who are infected with COVID-19 is the first step in the battle against it, and having examinations of chest X-rays. The research aimed to evolve a deep-learning method for the early identification of pneumonia and COVID-19 lung disease using chest X-rays. In this paper, a deep learning method has been proposed using an improved 53-layer residual network model. The COVIDx dataset with 13975 CXR images and the Kermany [17] dataset with 5856 CXR images has been used to evaluate the proposed models. In these image collections, a 4:1 aspect ratio is used for training and testing. The experimental results are performed using Python and results are compared and analyzed with pre-trained models such as GoogLeNet, ResNet50, and DenseNet121.The proposed model outperforms the most sophisticated models on the Kermany dataset with accuracy of 97.9%, sensitivity of 98.1%, specificity of 97.6%, and precision of 97%. The proposed model performance on the COVIDx dataset is 97.1%, 98.9%, 95.7% and 94.5% for accuracy, sensitivity, specificity and precision, respectively. Apart from that, we have also incorporated three more layers to ResNet50, creating it a ResNet50+3 layer design which resolves the vanishing gradient issue and, makes training easier. The result of the whole analysis shows that the proposed model not only outperforms most classifiers but is also a very generic system that is adjustable to a various healthcare datasets.

***Keywords*: *Covid-19, Pneumonia, machine learning, googlenet, resnet, densenet*.**

1. Introduction

Many people have died as a consequence of epidemics and chronic illnesses throughout history, creating enormous setback that took a very long period to address. When a disease spreads quickly through a population, the terms "epidemic" and "outbreak" are used to characterize the situation. A virus is defined as an occurrence of more and more cases of sickness, infections, or other health related difficulties than expected in a particular region or within a particular number of people at a particular time. The periods contend that they have a shared genesis in general. The scale of the outbreak is more constrained than that of an epidemic, and the word is less likely to arouse public concern [1], [2].

The health and well-being of individuals globally are still being ravaged by the coronavirus (COVID-19) epidemic. A significant advancement for battle against COVID-19 is the effective webbing of inflamed patients, with chest radiography being one of the main webbing techniques. Earlier studies have shown that chest radiography imaging is abnormal in COVID-19-infected people [2], [3].

[1]A lung infection called pneumonia that results in pleural effusion and inflammation of the air sacs is introduced by bacteria, or fungi (fluid in the lung), or viruses. More than 15 percentages of all pediatric mishappenings in infants under five years of age are due to this disease [1]. Pneumonia is more common in under-developed and impoverished nations where the disease made worse by pollution, traffic, and unfavorable surrounding conditions and there are few medical resources available. Thus, early detection and treatment can aid in preventing the ailment from developing into a deadly stage. Radiography, MRI (magnetic resonance imaging), and CT (computed tomography) are frequently used to evaluate the lungs (X-rays). An inexpensive, non-invasive method for evaluating the lungs is X-shaft imaging.

A range of challenging computer vision problems may be solved with the help of deep learning, a cutting-edge artificial intelligence technique [4], [5]. Convolutional neural networks (CNNs) are typical type of deep-learning model that is used to tackle a variety of picture classification problems. Similar models function exceptionally well when given a large quantity of data to work with. The development of transfer learning is one result of this conundrum. This method solves an issue with

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a small dataset by utilizing network cost (weights) provided by a model, trained on a big datasets. CNN models are widely used for natural picture bracketing since they have been trained on large datasets like ImageNet [6], which has over 14 million prints [22].

To tackle such kind of issue, in this paper, we have developed a model which will help in the early diagnosis of lung disease which has performed very well when compared with some pre-trained deep-learning models. This proposed model is explained in section III of this paper.

2. Related Work

In order to recognize patients with COVID-19 from normal occurrences, which may contain both non-positive and positive cases, DL frameworks developed on Chest-XR images have been proposed in a few literatures [7]. The later research within the field of lung disease diagnosis utilizing machine learning was evaluated in this contribution [8]. An outline of the foremost predominant lung conditions is given, including interstitial lung infection, pneumonia, aspiratory embolism, lung nodule disease, and tuberculosis (TB). A portable CNN texture architecture was made by Ali et al [9] for the categorization of lung nodule threat. The model was effectively trained utilizing six-fold cross-validation, with an astonishing result of 96.69%, 96.05%, 97.37%, 99.11% and 3.30%, for accuracy, recall, specificity, AUC and error rates, respectively. The work in [10] recommends a novel method based on multilayer thresholding and SVM with normal lung symptomatic affectability of 95.76%, specificity of 99.7%, and precision of 97.48%, individually, utilizing X-ray pictures to distinguish COVID-19. According to the author [11], ResNet152 may be utilized to classify deep features based on ML data assembled from CXR pictures of patients who had pneumonia and the COVID-19 infection. The model had an accuracy of 97.7% and 97.3% in XGBoost and Random Forest predictive classifiers, respectively. Authors in [12], [13] utilized gradient-weighted class activation mapping (Grad-CAM) [14] to highlight critical variations in chest CT images. Comparable to this, in paper [7] created heat maps of the rate of COVID-19 contamination in receptive areas by comparing chestCT image estimate and upsampling. The features of lung lesions on CT images were compared to the key clinical markers by Zhang et al. [15]. In arrange to rapidly recognize COVID-19 occurrences; in [18] authors proposed the nCOVnet approach, which is based on the thought of data leaking. In their research, they had an 88% detection accuracy. The authors of this study might not clearly outline any illustrations of COVID-19 that were seen on chest X-ray pictures. DeQueezeNet, a strategy presented by Kumar et al. [19], isolates patient radiographs into +ve and -ve categories and recognizes COVID-19. There model detects the possibility of illness with 94.52% and 90.48%, respectively, utilizing preprocessed CXR pictures of confirmed COVID-19 cases and negetive cases. In image classification issues, transfer learning has extraordinary results. Chest radiographs were utilized by the author in [20] to diagnose pneumonia and make further distinctions between those with and without the illness. With an accuracy rating of 0.843, the suggested model takes 36 conv-layers under consideration. In spite of the fact that there's a shortage of data, Apostolopoulos and Mpesiana [21] detailed utilizing transfer learning to recognize COVID-19. They had an accuracy rate of 96.78%. Kushagra et al. [22] proposed a genetic algorithm based approach on modified deeplearning model for lung disease diagnosis. The model has achieved 98.1% accuracy, 98.2% sensitivity, 97.9% specificity, and 97.6% precision.

3. Methodology

The architecture of the model has several levels. We started out by using two datasets which are accessible publicly. The generated CXR images are then subjected to a second degree of pre-processing. The third level of functionality of the proposed modified ResNet50+3 deep transfer learning model is incharge of selecting features from pre-processed CXR images and providing the categorization report. Lastly, the model's results were obtained from the parameters of precision, recall, sensitivity, and accuracy.

3.1 Dataset

In this study, we used the publicly accessible datasets COVIDx [16] and kermany [17] to assess our proposed model. Performance for multiple-class classification tasks was assessed using COVIDx, a publicly available dataset of COVID-19 CXR pictures. 13,975 chest X-ray (CXR) pictures are included in the dataset, and they are categorised as normal, non-COVID pneumonia, or COVID positive. Figure 1 displays the distribution of CXR pictures from the COVIDx dataset. Image examples for each diagnosis are shown in Fig 2. Additionally, COVID-19 positive case categorization is complicated by the striking visual resemblance between COVID-19 positive patients and non-COVID pneumonia cases. The Kermany dataset's 5856 images were divided into two categories: normal and pneumonia. Figure 3 displays the distribution of CXR pictures from the Germany dataset. These datasets are suitable for assessing the effectiveness of our suggested method in resolving the aforementioned issues.

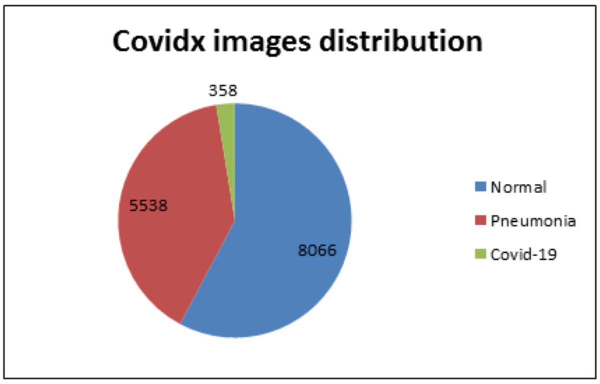

Fig 1 : COVIDx dataset images of chest X-rays distribution.

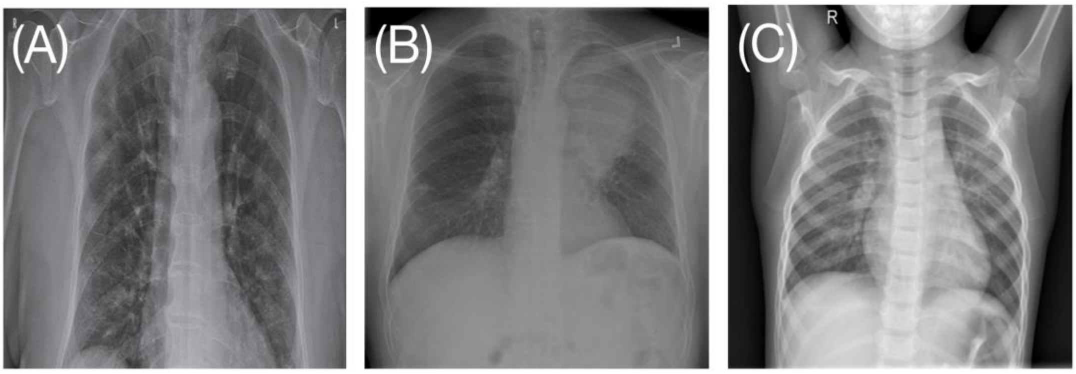

Fig 2: CXR images of (A) A positive case of COVID-19, (B) A case of Pneumonia, and (C) A normal healthy case in the COVIDx dataset.

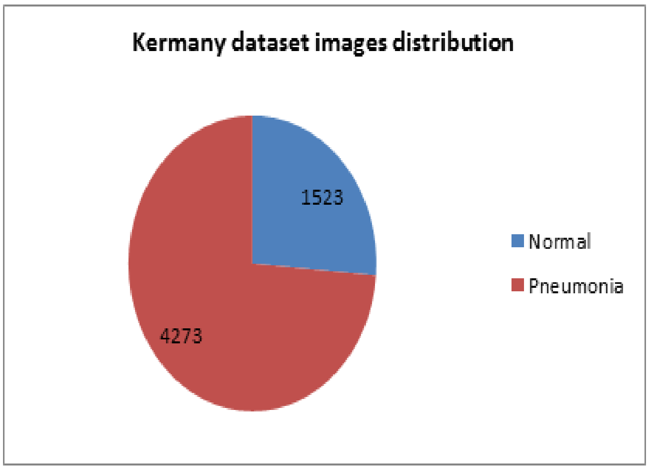

Fig 3: Kermany dataset images of chest x-rays distribution.

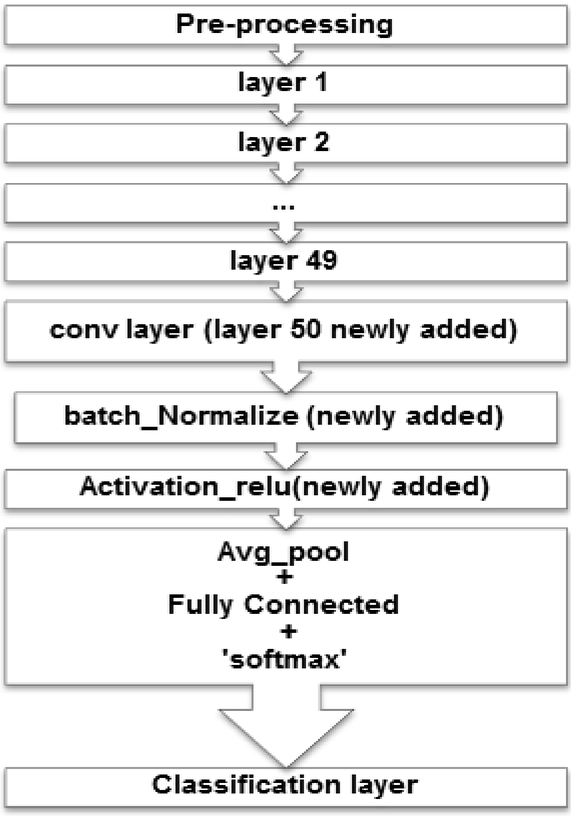

Fig 4: Proposed RESNET50+3 Model

3.2 Proposed model

In order to extract deep features, the proposed work for effective prediction disease from chest X-ray images relies on a single pre-trained fine-tuned deep CNN model. As shown in Fig. 4, we presented a modified ResNet50 CNN architecture. By adding several layers to the end of the ResNet50 architecture, it is adapted to the CXR dataset. CXR images are taken in low resolution with a variable aspect ratio. As a result, the images of the training and test datasets are resized to 224x224x3 to obtain compatibility in the model architecture created. The "ResNet" DL model is known as a better designed architecture because it is relatively easy to optimize and can achieve higher accuracy. Additionally, the vanishing gradient is always an issue, which is now resolved by using skipped network connections. As the number of layers in the deep NN design rises, the model's time complexity also does. This complication may be simplified by using a “bottleneck-design”. Therefore, we prioritized the pre-trained model ResNet50 to construct our framework and exclude other existing models that have a larger number of layers. A full explanation of the architecture follows in fig 4.

To obtain efficient performance for forecasting COVID-19, the ResNet50 architecture is modified. First, we modified the pretrained ResNet50 architecture's bottom 3 layers (completely connected, softmax, and classification layers) to better suit our classification objective. The original pretrained networks' fully-connected layer is replaced with another fully connected layer, with the output size matching the classification layer. Following that, 3-layers are added to the ResNet50 model architecture, namely CNN layer (conv layer), Normalization layer (batch_Normalize), & Relu activation layer (Activation_relu) as shown in Fig. 4, to automatize the extraction of the robust features in Xray images.

Then feature of each image of dataset is extracted when passed through this updated network, and the network classifier is used to classify them as Covid or NonCovid pneumonia or normal. As previously stated, the suggested model was trained for the categorization of lung illnesses using two publically accessible datasets.

3.3 Evaluation metrics

Four standard evaluation measures are used to assess the proposed technique on two sets of lung disease data: accuracy, precision, sensitivity, and specificity. Firstly, the words True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) are defined.

Suppose we have two classes of data labeled "positive" and "negative" for binary classification. True Positive (TP) is the quality standard by which the model is defined. A sample which wrongly predicted as negative but was positive in the actual dataset is known as false positive (FP). True Negative (TN) samples are those that are rightly classified as negative whereas False

Negative (FN) sample is wrongly identified as positive but was negative in real data [22].

The analysis of chest disease patients between Normal, Covid-19 or Pneumonia patients is termed as Accuracy, Sensitivity, Specificity, and Precision are represented mathematically in terms of confusion matrix as given here in eq. 1, 2, 3, 4, respectively. Here total correct predictions is TP+TN, totals cases are the sum of all the predictions by the model i.e. TP+TN+FP+FN, total correct positive predictions means TP, whereas total positive cases means TP+FN, total negative cases means TN+FP.

$$Accuracy = \frac{Total\ correct\ predictions}{Total\ cases} \quad (1)$$

$$Sensitivity = \frac{Total\ Correct\ positive\ predictions}{Total\ Positive\ cases} \quad (2)$$

$$Specificity = \frac{Total\ Correct\ positive\ predictions}{Total\ Negetive\ cases} \quad (3)$$

$$Precision = \frac{Total\ correct\ positive\ predictions}{Total\ positive\ predictions} \quad (4)$$

4. Result Analysis

The results of the proposed method are presented in this section. As indicated in the earlier section, we have modified a pre-trained model by adding some additional layers, which improves the model's overall performance. The proposed model is applied on two publically available chest radiograph datasets. While the task was very challenging as the pattern of pneumonia and covid-19 is very much similar but the proposed system demonstrates its superiority when were compared with existing state-of-art models. In fig 5 observations of proposed model on COVIDx dataset is shown which achieves a remarkable 97.1%, 98.9%, 95.7%, and 94.5% for accuracy, sensitivity, specificity and precision, respectively. While analysis of the existing techniques with proposed technique on the COVIDx dataset shown in table 1. The proposed model outperformed all state-of-art models.

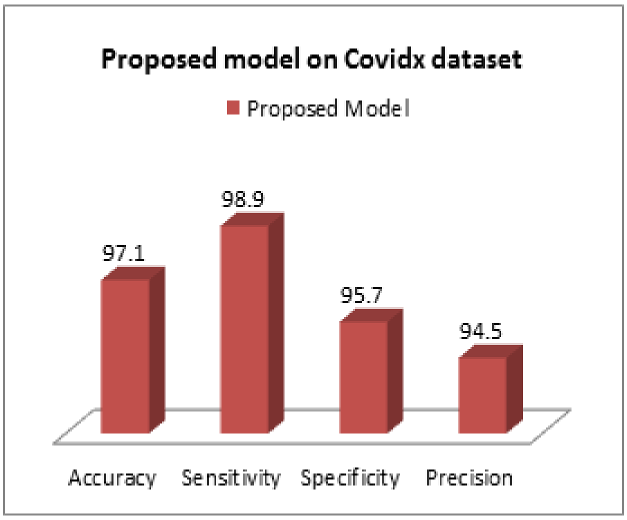

Fig 5: Result analysis of proposed method on Covidx dataset

Table 1: Analysis of proposed method with existing method on covidx dataset.

Model	Accuracy	Sensitivity	Specificity	Precision
denseNet-121	96.2	96.2	94	96.6
Resnet50	96.9	96.7	97.3	98.7
Googlenet	96.2	97.6	93.3	96.8
Vgg16	87.5	97	68	86.2
Proposed Model	**97.1**	**98.9**	**95.7**	**94.5**

In fig 6 accuracy comparison of different models on covidx dataset is shown. It is evident that accuracy of proposed model outperformed all existing models.

In fig 7 sensitivity comparison of different models on covidx dataset is shown. It is evident that sensitivity of proposed method exceeds all existing models.

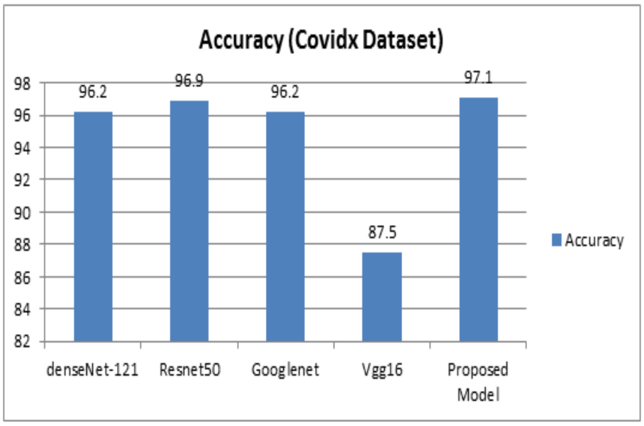

Fig 6: Accuracy analysis of proposed method on COVIDx dataset

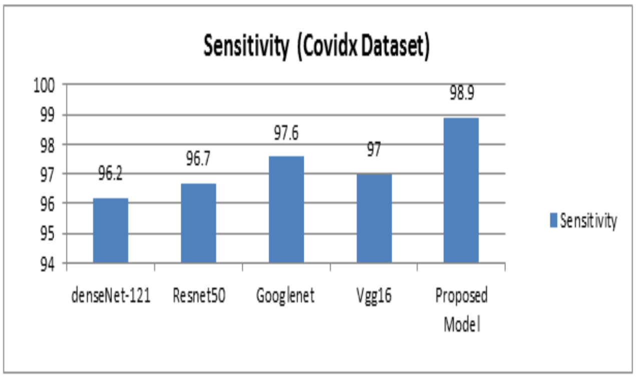

Fig 7: Sensitivity analysis of proposed method on COVIDx dataset

In fig 8 specificity comparison of different models on covidx dataset is shown. It is evident that specificity of proposed model exceeds all mentioned models.

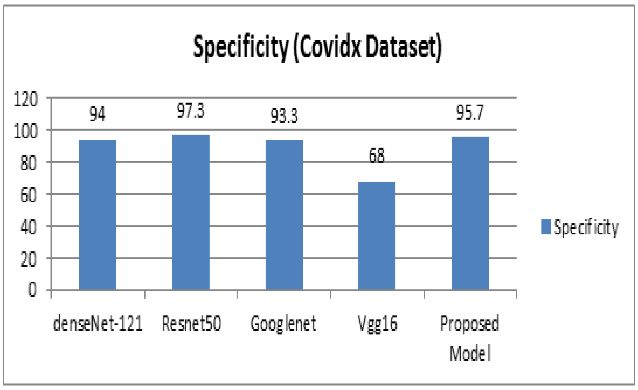

Fig 8: Specificity analysis of proposed method on COVIDx dataset

In fig 9 precision comparison of different models on covidx dataset is shown. It is evident that precision of proposed model exceeds all mentioned models.

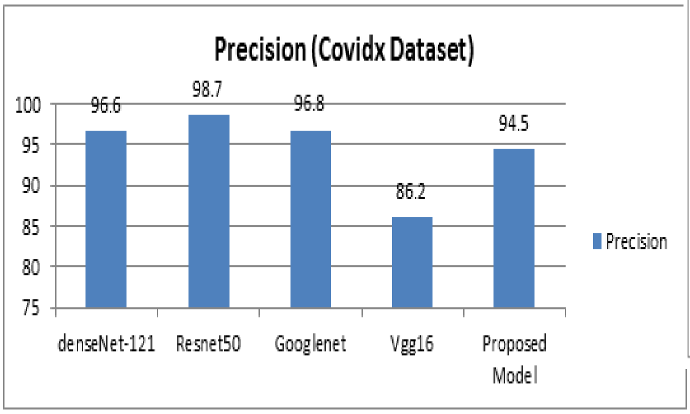

Fig 9: Precision analysis of proposed method on COVIDx dataset

Graphical findings of the proposed model on kermany dataset are shown in fig 10. Comparison of the proposed modified ResNet50 model with other pre-trained models on the kermany dataset is mentioned in table 2 shows excellent result with 97.9% accuracy, 98.1% recall, 97.6% specificity, and 97% precision which surpasses numerous state-of-the-art models.

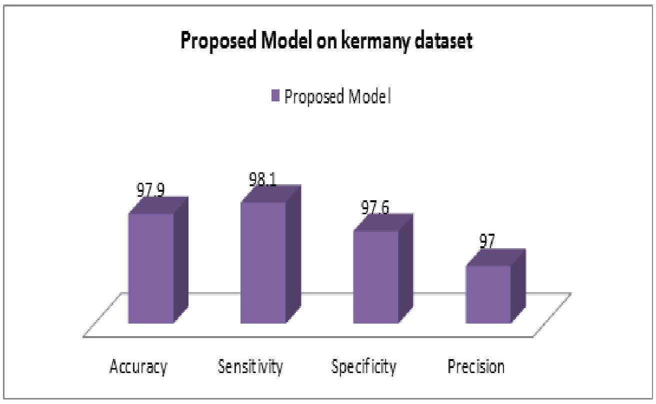

Fig 10: Result of proposed method on kermany dataset

Table 2: Analysis of proposed method with existing models on kermany dataset.

Model	Accuracy	Sensitivity	Specificity	Precision
denseNet-121	96.2	96.2	96.3	96.6
Resnet50	97.5	97.8	95.5	96.3
Googlenet	97.6	98.0	98.1	98.0
Vgg16	91.0	94.3	91.1	87.1
Proposed Model	**97.9**	**98.1**	**97.6**	**97.0**

In fig 11 accuracy comparison of different models on kermany dataset is shown. It is evident that accuracy of proposed model exceeds all existing models.

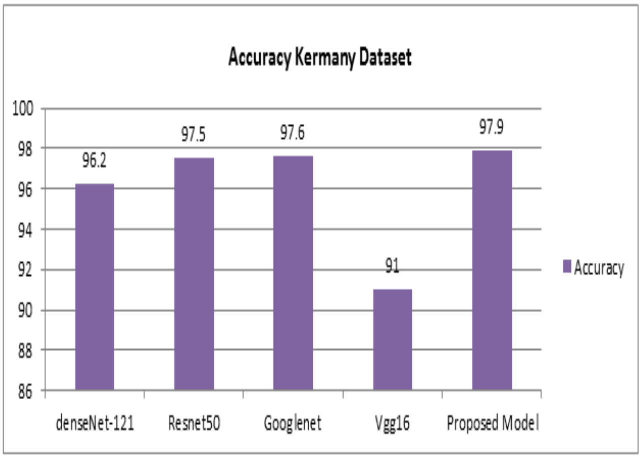

Fig 11: Accuracy of proposed method on kermany dataset

In fig 12 sensitivity comparison of different models on kermany dataset is shown. It is evident that sensitivity of proposed model exceeds all existing models.

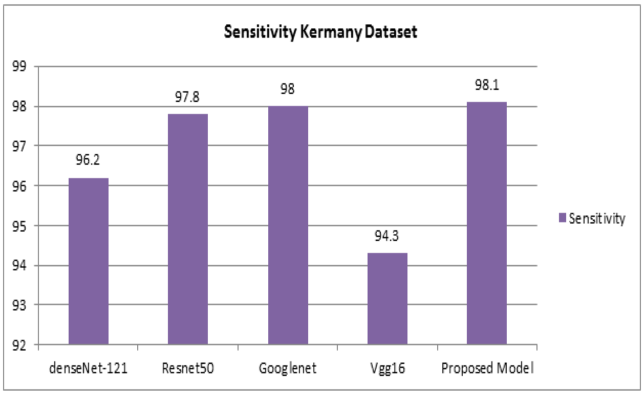

Fig 12: Sensitivity of proposed method on kermany dataset

In fig 13 specificity comparison of different models on kermany dataset is shown. It is evident that specificity of proposed model exceeds all mentioned models.

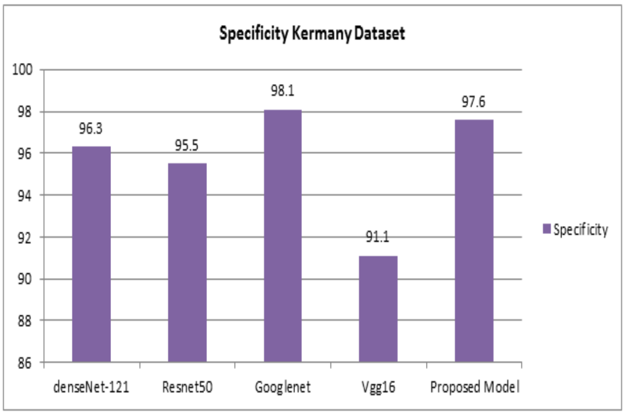

Fig 13: Specificity of proposed method on kermany dataset

In fig 14 precision comparison of different models on kermany dataset is shown. It is evident that precision of proposed model exceeds all mentioned methods.

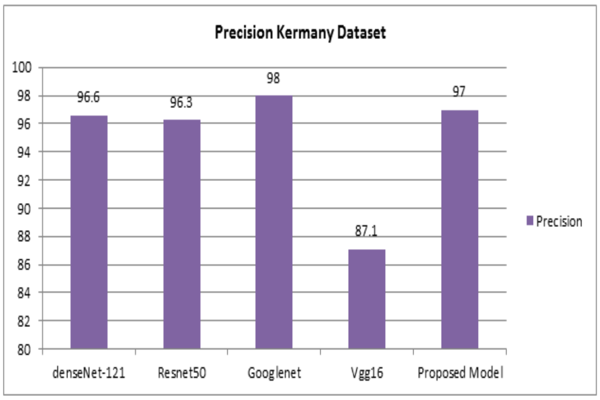

Fig 14: Precision of proposed method on kermany dataset

5. Conclusion

This article introduces the deep learning model "ResNet50+3". It is an updated version of the ResNet50 model with three additional layers and is a deep learning model for recognizing pneumonia (COVID-19, pneumonia). By adding three layers to ResNet50, results are better than the baseline. Prepared samples can detect lung disease more effectively and efficiently than other well-known methods. The proposed model overcomes the disappearing gradient problem of ResNet50 and thus improves the training model. This reduces the complexity of the network and increases accuracy. The accuracy of the model is 97.1%, its accuracy is 98.9%, its accuracy is 95.7% and its accuracy is 94%.It outperforms most existing models with 5% accuracy on the COVIDx dataset and 97.9% accuracy, 98.1% sensitivity, 97.6% specificity and 97% accuracy on the Kermany dataset. Our design pattern is a general pattern used in many computer games.

In the future, we may investigate some strategies to extract important regions from an image using appropriate image segmentation techniques or other pre-processing procedures to improve image quality. We can also segment lung photos prior to classification to help the CNN algorithm identify additional information.

Conflicts of interest

The authors declare no conflicts of interest.

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