An Efficient Deep-learning Model to Diagnose COVID-19 and Pneumonia using CXR Images: ResNet50+3

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Abstract: Coronavirus Disease-2019 (COVID-19) pandemic continues to have a severe impact on the worldwide public's health and well-being. Effective screening of contaminated individuals is a significant step in the fight against COVID-19, with radiologic evaluation employing chest radiography being one of the primary screening modalities. In preliminary research, it was discovered that patients with COVID-19 contamination have anomalies in chest radiography imaging. The goal of this work is to develop a deep-learning algorithm for early diagnosis of COVID-19 and pneumonia lung infections using CXR images. Methods: A deep transfer learning technique is given for image categorization using an improved Residual Network model with 53 layers, which is a variation of the ResNet-50 model. The model is evaluated using the COVIDx dataset, which contains 13975 CXR pictures, as well as the Kermany dataset, which has 5856 CXR images. 80% of the photos in this image collection are used for training, while 20% are utilised for testing. Python is used for implementation to illustrate the efficacy of the suggested paradigm. The performance results are analysed and compared to pre-trained models such as GoogLeNet, ResNet18, and DensNet121. Findings: On the Kermany dataset, the suggested model achieves 98.1% accuracy, 98.8% precision, and 98.8% recall, while on the COVIDx dataset, it achieves 97.1% accuracy, 98.9% recall, 95.7% specificity, and 94.5% precision, which is superior to the most advanced models addressed in the literature. Novelty: We have added three layers to ResNet50, making it a ResNet50+3 layer architecture. These three extra layers solve the vanishing gradient problem in the ResNet50 architecture, making it easier to train. According to the findings of the complete investigation, the suggested model not only surpasses most classifiers such as GoogLeNet, ResNet50, and DenseNet121 in terms of accuracy, precision, and recall, but it is also a very versatile model that works well on varied datasets.

Keywords: Machine Learning, Deep Learning, Covid-19, Pneumonia, x-ray images, googlenet, resnet, densenet, vgg.

I. Introduction

Epidemics and chronic diseases have claimed the lives of countless people throughout history, resulting in massive crises that took a long time to resolve. The phrases "epidemic" and "outbreak" are used to describe diseases that spread rapidly through a community. A virus can be described as the happening of more cases of disease, damage, or other health issues than anticipated in a given location or among a specific population of persons at some moment during a certain time period. In general, the eras claim to share a common aetiology. The outbreak differs from an epidemic in that its extent is more confined or the term is less likely to provoke public worry.

The coronavirus (COVID-19) outbreak is still decimating the worldwide people's fitness and well-being. Effective webbing of inflamed patients is a huge step forward in the fight against COVID-19, with radiological assessment via coffin radiography being one of the primary webbing approaches. Previously, researchers revealed that individuals infected with COVID-19 have abnormalities in coffin radiography imaging.

Pneumonia is a lung infection occurs by bacteria, viruses, or fungus that causes air sac inflammation and pleural effusion (fluid in the lung). It also accounts for more than 15% of all paediatric mortality in children under the age of five [1]. Pneumonia is more frequent in poor and disadvantaged nations where traffic, pollution, and unprintable environmental circumstances aggravate the illness and medical resources are few. As a consequence, early identification and treatment can help prevent the condition from progressing to a fatal stage. Computed tomography (CT), magnetic resonance imaging (MRI), or radiography are commonly used to assess the lungs (X-rays). X-shaft imaging, a non-invasive and frequently affordable tool, can be used to assess the lungs.

Deep learning is an advanced artificial intelligence method that can aid in the resolution of a variety of complicated computer vision issues [4, 5]. Deep learning models, namely convolutional neural networks (CNNs), are commonly employed to solve a wide range of image categorization challenges. When given a substantial amount of data to work with, comparable models perform excellently. Obtaining such a large amount of tagged data for biological image bracket problems is difficult due to the necessity for professional croakers, which is an expensive and time-consuming activity. One of the consequences of this dilemma is the rise of transfer literacy. Using network weights given by a model trained on a large dataset, this technique breaks a problem with a small dataset. CNN models trained on huge datasets, such as ImageNet [6], with over 14 million prints, are frequently employed for natural picture bracketing.

The rest of the paper is organised as follows: Section 2 discusses related work. The approach is covered in Section 3, which covers an introduction to datasets, preprocessing, and deep learning model creation. The fourth section dives into the experimental results and interpretation. Finally, in Section 5, we will wrap up our work.

II. Related work

Several investigations have proposed DL systems formed on CXR imaging to distinguish patients with COVID-19 from non-COVID-19 cases (that may include both normal and positive cases) [7]. In this contribution, the most current works in the field of machine learning for the detection of lung diseases were evaluated [8]. An overview of the most common lung diseases is offered, including lung nodule disease, pulmonary embolism, pneumonia, TB and interstitial lung disease. Ali et al [9] developed a portable CNN texture architecture for lung nodule malignancy classification. Six-fold cross-validation was used to effectively train the model, resulting in precision96.69%, recall96.05%, specificity97.37%, AUC99.11%, and error rates of3.30% respectively. The study in [10] proposes a unique approach to detect COVID19 for X-ray images based on multilayer thresholding and SVM with average lung diagnostic sensitivity95.76%, specificity99.7% and accuracy of97.48%, respectively. The author [11] proposed to use ResNet152 to categorize deep features based on ML collected from CXR images of patients with COVID19 and pneumonia. The model achieved 97.3% accuracy in Random Forest and in XGBoost predictive classifiers 97.7% accuracy. Gradient-weighted Class Activation Mapping (Grad-CAM) [14] was used by Ai et al. [12] and Jin et al. [13] to visualize significant differences in chest CT images. Similarly, Mei et al. [7] used upsampling to compare chest CT image size to create heat maps of the rate of COVID-19 infection in receptive fields. Zhang et al. [15] investigated the relationship between the main clinical indicators and the characteristics of lung lesions on chest CT images. Panwar et al. [18] presented the nCOVnet technique, which is based on the principle of data leakage, for rapid detection of COVID-19 situations. They achieved 88% detection accuracy in their studies. The authors in this study did not provide clear visualization of identified cases of COVID-19 on chest x-ray images. Kumar et al. [19] presented DeQueezeNet, a model that classifies patient radiographs into two categories: positive and negative, identifying COVID-19. By preprocessing CXR images of positive COVID-19 patients and normal cases, the proposed model predicts the probability of disease with accuracy of 94.52% and 90.48% accuracy, respectively. Transfer learning has shown excellent results in image classification problems. Author in [20] used chest radiographs to identify pneumonia and further distinguished between individuals infected with pneumonia and those who were not. The proposed model considers thirty-sixconv-layers and has an accuracy score of 0.843. As there is a limited amount of data available, Apostolopoulos and Mpesiana [21] reported the use of transfer learning in the detection of COVID-19. They achieved 96.78% accuracy.

III. Methodology

The model architecture is multi-leveled. At the most basic level, we used two publicly available datasets. The resulting CXR pictures are subsequently pre-processed at the second level. The suggested updated ResNet50+3 deep transfer learning model's third level of functionality is in charge of choosing features from preprocessed chest X-ray pictures and sending the classification report. Finally, the model's findings were generated in terms of accuracy, sensitivity, recall, and precision.

A. Dataset

In this work, we evaluated our suggested model using publically available datasets COVIDx [16] and kermany [17]. COVIDx, a public COVID-19 CXR images dataset, was used to evaluate performance for multiple-class classification tasks. Dataset includes 13,975 chest X-ray (CXR) images categorised as COVID positive, non-COVID pneumonia, or normal. Distribution of CXR images of COVIDx dataset is shown in fig 1. Fig2 depicts image samples for each diagnosis. Furthermore, COVID-19 positive patients and non-COVID pneumonia cases have strong visual similarities, making COVID-19 positive case classification problematic. The 5856 pictures in the Kermany dataset were categorised into two categories: normal and pneumonia. Distribution of CXR images of kermanydataset is shown in fig 3. These datasets are appropriate for evaluating the efficacy of our proposed technique in overcoming the aforementioned difficulties.

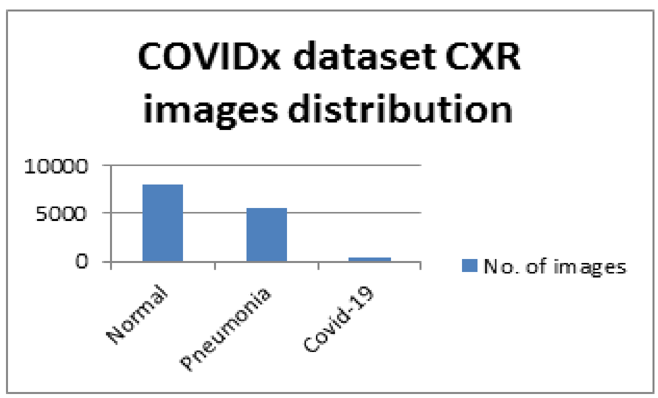

FIG 1 : CXR IMAGES DISTRIBUTION OF COVIDX DATASET.

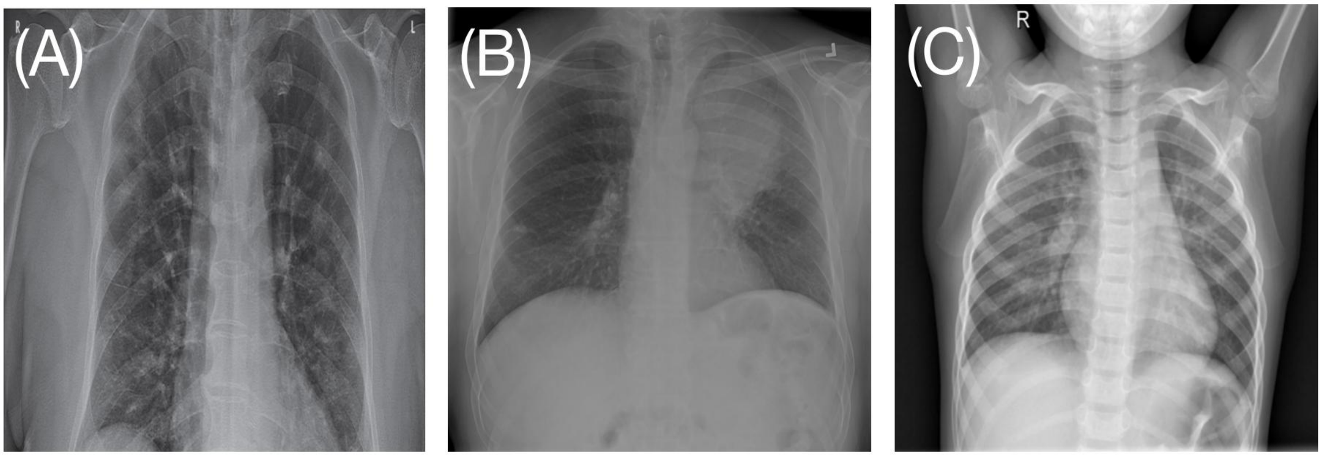

FIG 2: CXR IMAGES OF (A) A POSITIVE CASE OF COVID-19, (B) A CASE OF NON-COVID-19 PNEUMONIA, AND (C) A NORMAL HEALTHY CASE IN THE COVIDX DATASET

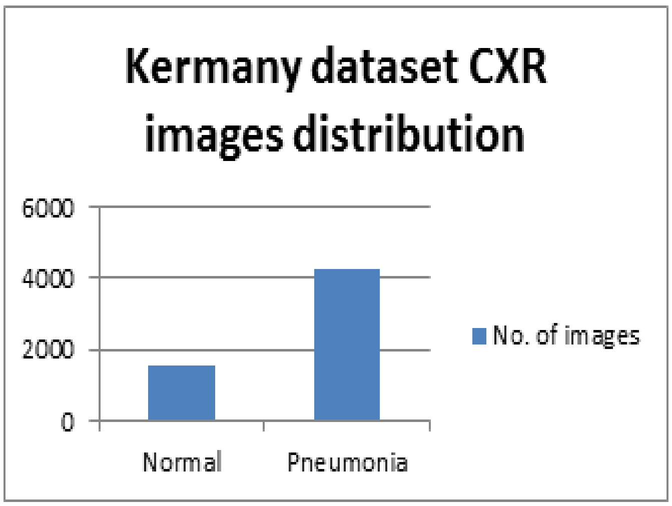

FIG 3: CXR IMAGES DISTRIBUTION OF KERMANY DATASET.

B. Proposed model

In order to extract deep features, the proposed framework for effective prediction of lung diseases such as COVID19 and pneumonia 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. The time complexity of the network increases as the number of layers in the deep network architecture increases. This complication can be simplified by using a “bottleneck-design”. As a result, we prioritized the ResNet50 pre-trained model to construct our framework and exclude other pre-trained networks that have a larger number of layers. A full explanation of the architecture follows.

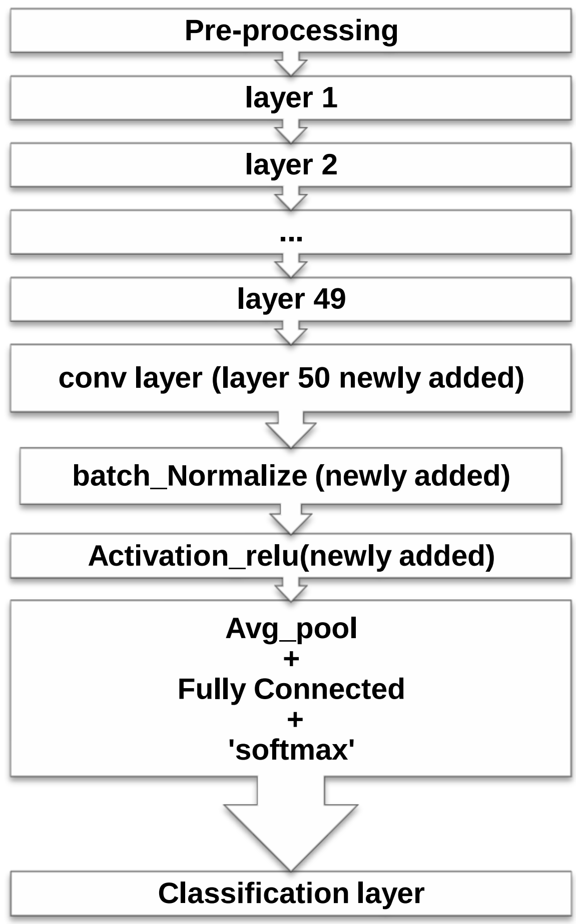

FIG 4: RESNET 50 MODIFIED WITH AN EXTRA 3-LAYER

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 "conv_layer," "batch_Normalize," & "Activation_relu," as shown in Fig. 4, to automatethe extraction of the robust features in chest Xray. These layers are the conv_layer, a batch batch_Normalize layer, and an Activation_relu layer. The three layers are joined together as follows:

1. The “Activation_relu_49” layer is separated from the “Avg_pool” layer and linked to the newly created “Conv_layer”.
2. The “Activation_relu” layer, which was just introduced, is linked to the “Avg_pool” layer.
3. Following the “Avg_pool” layer are the three newly added layers “Fully_connected”, “softmax”, and “Classification_Layer”.

The input photos are then sent through this updated network to extract features for each image in the dataset, 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.

C. Evaluation metrics

Four standard assessment metrics were utilised to evaluate the suggested technique on the two chest disease datasets: accuracy, precision, recall, and f1-score. To begin, the words "True Positive," "False Positive," "True Negative," "False Negative," and "False Negative," as well as the phrases "True Positive," "False Negative," and "False Negative," will be defined.

Assume the two classes in the dataset are labelled "positive" and "negative" for a binary classification job. The following are definitions for the ideas discussed above. A True Positive (TP) is a positive-class sample that a model accurately identifies. A false positive (FP) sample is one that should have been labelled negative but was labelled positive instead. True Negative (TN) samples are those that are classified as negative.

IV. EXPERIMENTAL RESULT

The results of the evaluation of the suggested updated ResNet50 model are displayed in this section. As mentioned in the preceding section, we have added three extra layers to the Modified ResNet50 model, which enhances the model's overall performance. This technique was used to detect a new coronavirus (COVID-19) and pneumonia in two freely available chest radiograph datasets. Although the task was very challenging as the pattern of pneumonia and covid-19 are very much similar. The suggested system was compared to pre-trained state-of-art models to demonstrate its superiority. Fig 5 depicts the findings of our proposed model on COVIDx dataset achieving a 97.1% accuracy level, 98.9% recall, 95.7% specificity, and 94.5% precision. While comparison of the proposed technique withexisting methods on the COVIDx dataset shown in table 1, it is obvious that our suggested model surpassed all existing models, which is clearly outstanding and ranks as the top model among all others. Graphical representation of the result is shown in fig 6.

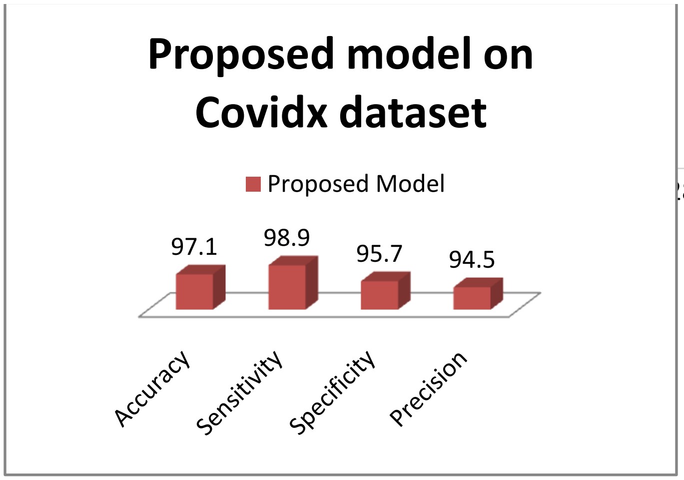

FIG 5: RESULT OF PROPOSED MODEL ON COVIDX DATASET

TABLE 1: COMPARISON OF PROPOSED METHOD WITH EXISTING MODELS 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**

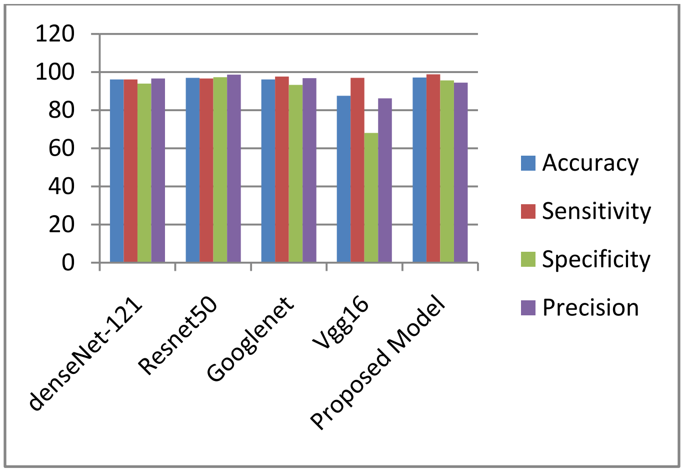

FIG 6: RESULT ANALYSIS OF PROPOSED MODEL ON COVIDX DATASET

Graphical findings of the proposed model on kermany dataset are shown in fig 7. 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. Comparison is shown in fig 8. This clearly shows that our suggested model is general in nature and that it can be applied to diverse datasets to obtain real outcomes in comparison to its rivals.

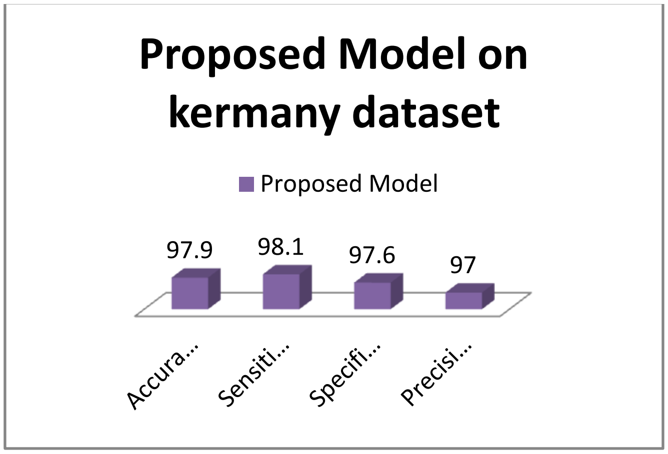

FIG 7: RESULT OF PROPOSED MODEL ON KERMANY DATASET

TABLE 2: COMPARISON 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**

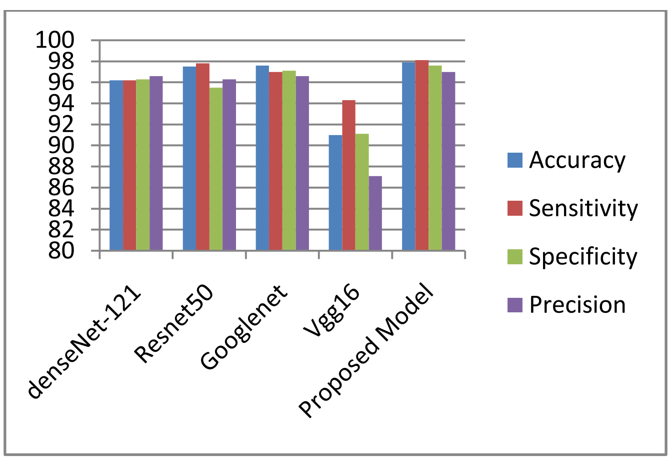

FIG 8: RESULT ANALYSIS OF PROPOSED MODEL ON KERMANY DATASET

V. CONCLUSION

In this study, a modified ResNet50+3 model is proposed, which is an effective deep transfer learning model for lung disease identification (COVID-19, Pneumonia). Adding three more layers to ResNet50 enables more robust feature extraction.When compared to other well-known approaches, the suggested model detects and performs better for lung disease infection. The suggested model overcomes ResNet50's vanishing gradient problem, resulting in improved model training. This decreases the network's time complexity and improves accuracy. Our technique was tested on the COVIDx and Kermany datasets. We attained 97.1% accuracy, 98.9% recall, 95.7% specificity, and 94.5% precision on the COVIDx dataset, and 97.9% accuracy, 98.1% recall, 97.6% specificity, and 97% precision on the Kermany dataset, exceeding most state-of-the-art models. Similarly, because we want the suggested model to be general, it may be used to a wide range of computer vision challenges.

In the future, we may look at some tactics for image discrepancy improvement or other pre-processing processes to improve image quality. We may also partition the lung picture before categorising it to help the CNN algorithms value extra information.

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