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Novo-NEX: A Tailored Self-Attention Deep Convolutional Neural Network for the Detection of Disparate Morbidity

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Abstract: COVID-19 also known as Severe Acute Respiratory Syndrome Corona virus-2 is a contagious disease that is released from tiny droplets containing saliva or mucus from respiratory system of a diseased person who talks, sneeze, or cough. It spreads rapidly through close contact with somebody who is infected or tapping or holding a virus contaminated objects and surfaces. Another infectious illness known as Pneumonia is often caused by infection due to a bacterium in the alveoli of lungs. When an infected tissue of the lungs has inflammation, it builds-up pus in it. To find out if the patient has these diseases, experts conduct physical exams and diagnose their patients through Chest X-ray, ultrasound, or biopsy of lungs. Misdiagnosis, inaccurate treatment, and if the disease is ignored will lead to the patient's loss of life. The progression of Deep Learning contributes to aid in the decision-making process of experts to diagnose patients with these diseases. The study employs a flexible and efficient approach of deep learning applying the Novo-NEX model in predicting and detecting a patient unaffected and affected with the disease employing a chest X-ray image. The study utilized a collected dataset of 7,181 images using a 256 x 256 image resolution with 32 batch size is applied to prove the performance of the Novo-NEX model being trained. The trained-model produced an accuracy rate of 92% during the performance training. Based on the result of testing conducted, the research study can detect and predict COVID-19, bacterial, and viral-pneumonia diseases based on chest X-ray images.

Keywords: COVID-19, efficient, patient, conducted, Novo-NEX

1. INTRODUCTION

Corona-virus or COVID-19 was confirmed by the World Health Organization a crisis on global health or pandemic considering the scope of its span on a global scale and a highly contagious disease [1]. The government in different countries has imposed stringent precautionary actions to combat the coverage and intensity of spreading of the virus like flight-restrictions, physical-distancing, border-restrictions, and practicing good personal hygiene. The corona-virus can be contaminated through breathing droplets released by a person who is chatting, sneezing, or coughing [2]. It spreads rapidly when there is close interaction with the infected person or by affecting infected surfaces and objects [3]. The best way to protect a person from a virus is by avoiding being exposed since until now there is no vaccine to combat the COVID-19 [3]. However, there are on-going researches and trials for potential treatment being conducted by scientists as of today [4]. More than 18 million infected cases of COVID-19 around 213 countries around the world [1]. It also claimed almost 700 thousand fatalities and around 12 million recoveries as of August 2020 [1].

Pneumonia can be a life-threatening illness if not diagnose properly and can result in the death of a person associated with this kind of ailment [5]. It is in a form of severe respiratory illness caused by transmittable agents like viruses, or bacteria that affects the lungs [5]. It can be spread through the nose or throat and affect the lungs if they are inhaled or communicated through air-borne droplets from a person coughing or sneezing [6]. The lungs of a person are made up of small sacs or alveoli that supplies the air passage whenever a well fit person breathes [5]. When a person is infected with pneumonia, it limits the oxygen intake and makes breathing difficult and painful due to tissue soreness caused by alveoli covered with fluids or pus [6]. An aging person from 50 years of age and above and kids under five years of age are susceptible to pneumonia illness for they have a weaker immune system and it has taken over a million lives globally [5]. In the Philippines, it has reported nearly 58,000 mortalities in 2016 and the 3rd top killer behind heart diseases and cancer.

COVID-19 signs and indications are almost identical to the pneumonia, if not properly diagnose will lead to incorrect diagnosis now that many hospitals around the world are congested. Many of these hospitals are working 24/7 due to massive increase of infections and most of its medical personnel are also infected with the virus [4]. Imprecise findings of pneumonia or non-COVID-19 may be labeled incorrectly as COVID-19 infected and setbacks in proper treatment are costly, the struggle and risk of being exposed to other positive patients of COVID-19.

Infected patients require an instantaneous medical response and efficient examination to stop the further wide spreading of COVID-19. The utmost method in the clinical examination for COVID-19 patients is Reverse Transcription-Polymerase Chain Reaction (RT-PCR) that employs respiratory-specimen samples for testing [7] and reference as the basic method for detection. Nevertheless, this procedure is conducted manually, difficult and timewasting process with an accuracy rate of 63% only [7]. Besides, there is a deficiency in RT-PCR supply kits for its demand in the market and hinders the efforts in the prevention of the disease [6]. Other methods in diagnosing COVID-19 includes laboratory analysis, epidemiological history, Chest Radiograph or CXR, and pathogenic testing. Bronco-pneumonia which triggers fever, coughing, dyspnea, and respiratory failure is one of the characteristics of severe COVID-19 infection [8]–[9]. Radiological imaging that is easily available in most hospitals is one significant diagnostic instrument for COVID-19. The radiologist captures a chest image of the patient through a radiograph instrument. A radiograph image is generated through radiation on a thin-skinned film to validate patients infected with disease or not-infected. Even though usual CXR images could assist early signs of suspected cases, the images of various related viral-pneumonia are similar, and they interrelate with other contagious lung illnesses. Hence, for a radiologist, it is not easy to distinguish COVID-19 to other related viral-pneumonia.

Convolutional Neural Networks (CNNs) have shown to be tremendously valuable in feature-extraction and learning through training and for that reason, it is commonly implemented in medical researches [5][6]. The application of CNN has improved the image attributes in the environment with low-light conditions, efficient endoscopy video, lung nodule detection and identification thru computed tomography images, analysis of pediatric-pneumonia through X-ray image of chest, and other pulmonary related studies. Methods of Deep learning covering the deep CNNs techniques on X-Ray images of chest are receiving recognition and encouraging outcomes has made it known in diverse applications.

The remainder of the disquisition is structured as follows: the review of literature is found in Section II. Section III describes the envisaged neural network, the chest roentgen ray datasets used, and the performance measures. In Section IV, the outcomes of the suggested paradigm are discussed. The work is concluded in Part V.

2. LITERATURE SURVEY

In recent years, deep learning models have proven to be a promising method in the field of medicine for the diagnosis of pathologies, including lung pathology, which is the focus of this study, and have also given very promising results in the diagnosis of other medical diseases [11][12][13]. A convolutional neural network was developed from the visual context studies neocognitron in 1980 by K. Fukushima [14]. In 1998, Yann Lecun, Leon Bottou, and Yoshua Bengio recorded a very important milestone in convolutional neural networks by introducing the architecture called LeeNet-5 [15], which is now widely used for handwritten recognition tasks. For this reason, we used a convolutional neural network in this study to diagnose the presence of COVID-19 and pneumonia. As the diagnosis of those diseases can be a tedious task, even among expert radiologists, this study aims to help radiologists diagnose COVID-19 and pneumonia from chest X-ray images easily and within a short time.

Several different algorithms have been proposed to diagnose the presence of COVID-19 and pneumonia in chest X-ray images and computer tomography (CT) scan images using different approaches with deep learning models, some of which are described below.

Li et al. [10] used CheXNet, DenseNet, VGG19, MobileNet, InceptionV3, ResNet18, ResNet101, and squeezeNet architecture to train the 3-class classification using transfer learning. The paper used data augmentation techniques on the dataset consisting of chest X-rays from 423 COVID-19 cases, 1,485 viral pneumonia cases, and 1,575 normal cases, and their model attained an accuracy of 97.94%. Li et al. [3] proposed a network architecture called CovXNet to diagnose the presence of COVID-19, viral pneumonia, and bacterial pneumonia. Their dataset consisted of 1,583 normal X-ray images, 1,493 non-COVID-19 viral pneumonia X-ray images, 2,980 bacterial pneumonia X-ray images, and 305 COVID-19 X-ray images cases from different patients. Their model performance had an accuracy of 89.1%. Gunraj et al. [16] proposed a COVID-Net network to diagnose the presence of COVID-19 and non-COVID-19 pneumonia. They introduced a new dataset of 13,975 chest X-ray images from 13,870 patients, and their model attained a performance accuracy of 93.3%. However, the paper only presented accuracy as the performance metric for the 3-class classification. Han et al. [17] used an attention-based deep 3D multiple instance learning (AD3D-MIL) approach for the screening of COVID-19 pneumonia from other forms of viral pneumonia. The researchers used a dataset of computer tomography (CT) scans that included 230 CT scans of COVID-19 from 79 patients, 100 CT scans of patients with pneumonia, and

130 CT scans from people who did not have pneumonia. They reported that their algorithm achieved an overall accuracy of 97.9%. Rajaraman et al. [18] presented an iteratively pruned deep learning model ensemble to detect COVID-19 in chest X-ray images. They trained two models in their research. The first one was trained to classify normal and abnormal chest X-Rays, while the second model was trained to classify COVID-19 and pneumonia cases by using the training weights of the first model with the help of the transfer learning method. They used the ensemble method to improve the prediction performance of their model and achieved an accuracy of 99.01%. Hammoudi et al. [19] presented tailored models for early-stage detection of COVID-19 pulmonary symptoms. Their models were trained with a dataset that included bacterial pneumonia, viral pneumonia, and normal chest X-ray images. Ko et al. [20] proposed a simple 2D deep learning framework called the first-track COVID-19 classification network (FCONet) to diagnose COVID-19 pneumonia on a single chest computer tomography (CT) scan image. They used the transfer learning approach with state-of-the-art deep learning models as the backbone for training the FCONet model. In all the pretrained FCONet models, ResNet50 FCONet had the highest performance results of 99.8%, 100%, and 99.87% for sensitivity, specificity, and accuracy on the test dataset, respectively.

In [21], image feature descriptors, feed-forward NN, and CNN that used COVID-19 CXR images for the identification of diseases were presented. [22] presented a deep convolutional neural network based on Xception architecture called CorNet for the detection of COVID-19 infections using CXR images. [23] presented a clinical predictive model that uses deep learning and laboratory data for estimating COVID-19 diseases. The model was tested with 18 laboratory findings from 600 patients. [24] presented deep transfer learning for detecting COVID-19 diseases using CXR and CT images. In [25], a hybrid CNN was presented using an optimization algorithm for diagnosing COVID-19. [26] presented a deep learning assisted method for the diagnosis of COVID-19. A comparative study of eight CNN models was presented. [27] used deep learning to detect COVID-19 on CXR. The system was composed of three phases. In the first phase, the presence of pneumonia was detected, then COVID-19 and pneumonia were determined, and lastly, the localization of diseases was performed. The paper used 6,523 CXR images and obtained an accuracy of 97%. [28] presented an AI system for predicting COVID-19 pneumonia using CXR images. [29] used transfer learning and semisupervised adversarial detection to classify COVID-19 from CT images. [30] introduced CCSHNET to classify COVID-19 using transfer learning and discriminate correlation analysis. They achieved the highest sensitivity of 98.3% and reported that CCSHNET outperformed 12 state-of-the-art COVID-19 detection models. [31] presented a patch-based CNN to diagnose COVID-19 in CXR images; their model achieved state-of-the-art performance.

3. METHODOLOGY

3.1. Dataset Description

The dataset utilised to train and assess the proposed Novo-NEX consists of 7181 chest radiography images in total. We integrated and modified five different publically available data sets to create this dataset: (1) COVID-19 Image Data Collection[32], and (2) COVID-19 Chest X-ray Dataset Initiative[33], both of which were developed in cooperation with Fig. (3) The ActualMed COVID-19 Chest X-ray Dataset Initiative[34], which was founded in conjunction with ActualMed, (4) The RSNA Pneumonia Detection Challenge dataset[36], which made use of publically available CXR data from[37], and (5) the COVID-19 radiography database[35]. Utilising the following patient case types from each of the five data repositories, we integrated and modified the data from the five sources to produce the dataset:

- Non-COVID19 pneumonia patient cases and COVID-19 patient cases from the COVID-19 Image Data
- Collection[32]
- COVID-19 patient cases from the Fig. 1 COVID-19 Chest X-ray Dataset Initiative[33],
- COVID-19 patient cases from the ActualMed COVID-19 Chest X-ray Dataset Initiative[34]
- Patient cases who have no pneumonia (i.e., normal) and non-COVID19 pneumonia patient cases from RSNA
- Pneumonia Detection Challenge dataset[36]
- COVID-19 patient cases from COVID-19 radiography database[34]

The distribution of images and patient cases amongst the different infection types shown in Figure 1, respectively.

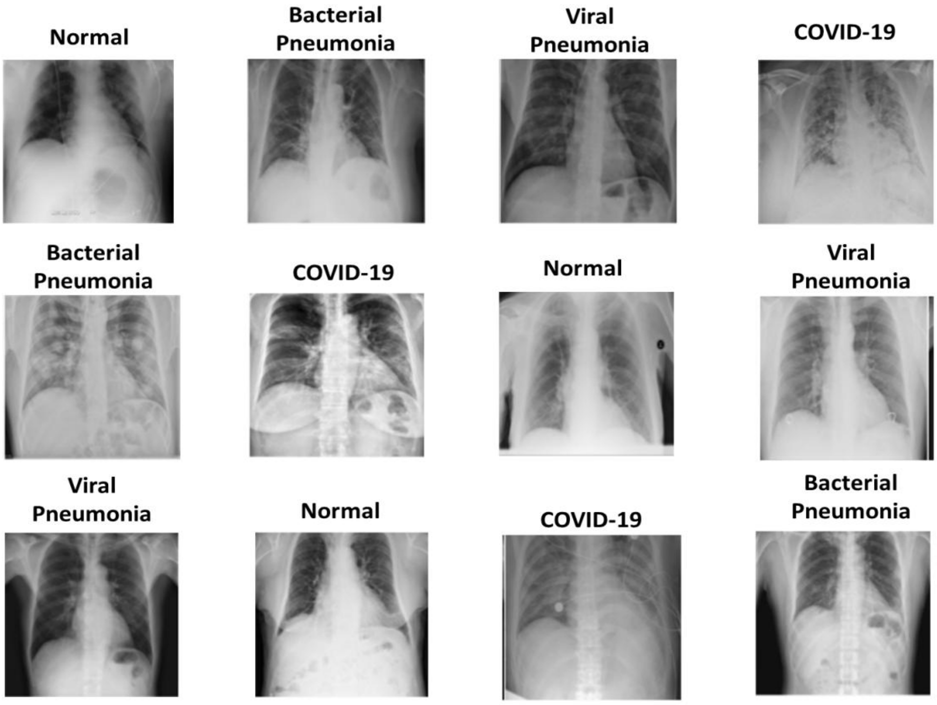
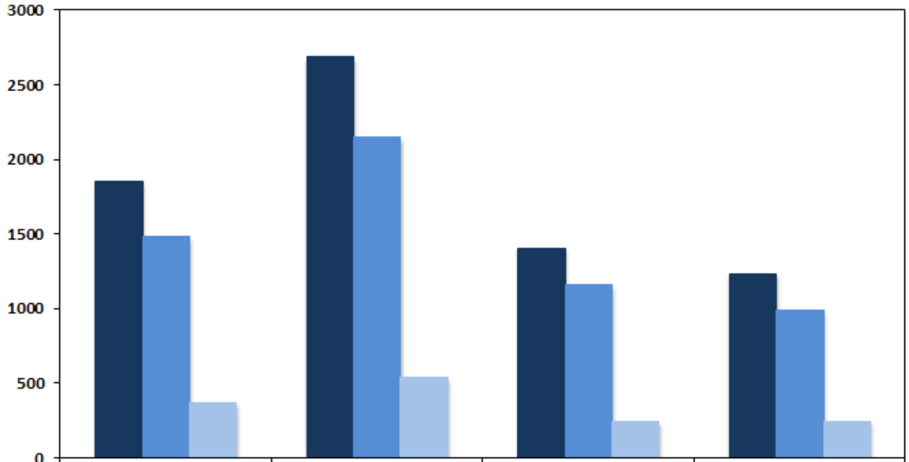


Figure 1. CXR images of: Normal, Viral Pneumonia, Bacterial Pneumonia and Covid-19 Cases

The images are then normalized and transformed to a (256, 256) format. The dataset are now rearranged and split into test and preliminary data. Thus, there are 5781 images and four classes in the training part. The same test part contains four categories and 1400 images. It is quite possible that the same patient's chest radiography images are kept in both the training and test parts, and it is indeed promising that the potentiality of the trained model is determined by the training of a validated and tested model, even though there may be overlap. Figure 2 below shows the chest x-rays of patients who were diagnosed as Normal, Viral Pneumonia, Bacterial Pneumonia or Covid-19 Cases.



	Normal	Baterial Pnemonia	Viral Pnemonia	COVID-19
Total	1853	2687	1405	1236
Train	1482	2150	1160	989
Test	371	537	245	247

Figure 2. CXR images distribution for each infection type of the dataset (normal means no infection).

3.2. Proposed Neural Network

Machine-vision tasks benefit from the use of deep convolutional neural networks. They have achieved progress in a variety of industries, including disease identification, medicine, and agriculture. The robust and significant semantic features that these networks produce from the incoming data are what give them their excellence. In this case, deep networks are primarily concerned with identifying infections in x-rays, hence x-rays are classified as normal, Bacterial Pneumonia, Viral Pneumonia and Covid-19.

The pre-processed input images of our dataset are 256 × 256 pixels. The Novo-NEX model consists of two phases. The first phase generates an output of size 1x1 on its last feature extractor layer from the input image, and the phase two also produces the output of same size on its final layer. As both networks generate the same size of feature maps, we concatenated their features so that by using both of the inception-based layers and residual-based layers, the quality of the generated semantic features would be enhanced.

A proposed network is designed by concatenating the extracted features of phase one and phase two and then connecting the concatenated features to a convolutional layer that is connected to the classifier. The kernel size of the convolutional layer that was added after the concatenated features was 1 × 1 with 1024 filters and no activation function. This layer was added to extract a more valuable semantic feature out of the features of a spatial point between all channels, with each channel being a feature map. This convolutional layer helps the network learn better from the concatenated features extracted from phase one and phase two. The architecture of the concatenated network is depicted in Fig. 3

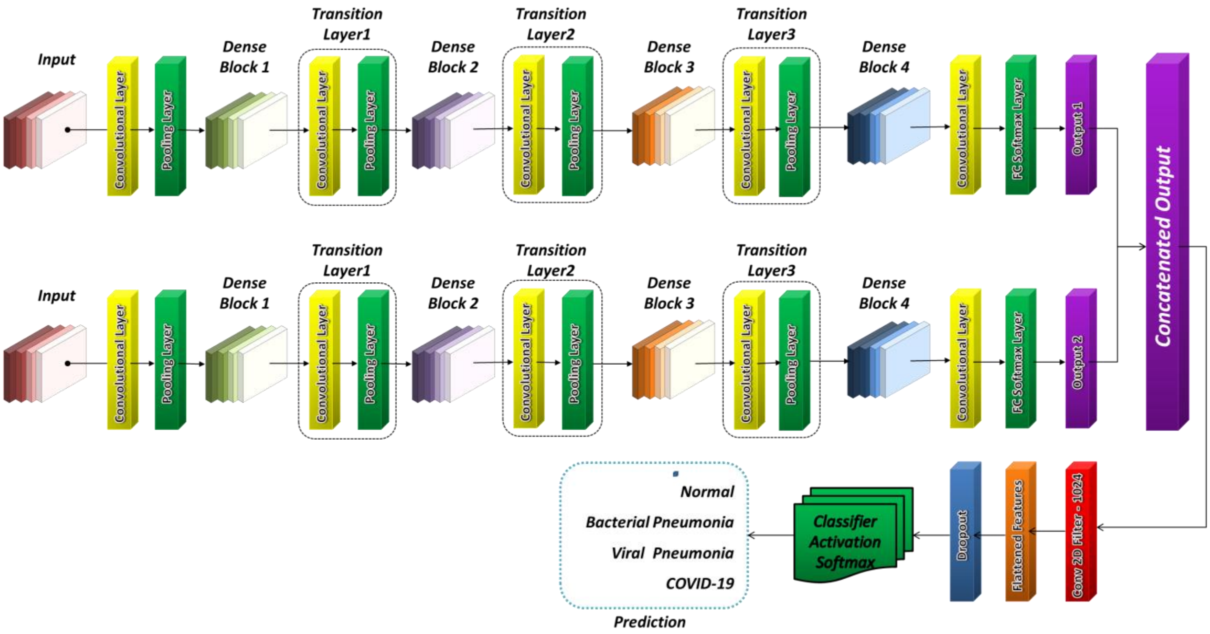


Figure 3. Architecture of Novo-NEX Model

3.3. Performance Metrics

3.3.1. Confusion Matrix

Although it is not regarded as a metric, the confusion matrix is a fundamental component that can be used to assess how well a machine learning classification model performs. It is a two-dimensional array that shows both real and predicted values in nature.

- True Positive (TP) is a category that is predicted to be true but also happens to be true (2019-nCov patients confirmed with 2019-nCov).
- True Negative (TN) is a category that is projected to be false but is also false in reality (patients who are healthy but are labeled as such).
- False Positive (FP) is a category that is predicted to be true but is actually false (healthy patients with COVID-19) and
- False Negative (FN) is a category that is predicted to be true but is actually false (patients who have COVID-19 but are healthy).

3.3.2. Accuracy

The number of precise predictions the model makes across all categories of predictions indicates accuracy in classification techniques.

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

3.3.3. Precision

The number of accurate positive predictions is known as precision. To make this calculation, divide the total number of predicted true positives (TP) by the sum of predicted true positives (TP) and false positives (FP).

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

3.3.4. Recall

Recall displays the percentage of accurate positive predictions among all possible positive predictions made by the model. To determine this, divide the total number of true positives (TP) in the dataset by the sum of true positives (TP) and false negatives (FP). Recall, in contrast to the accuracy measure, indicates positive predictions that were not fulfilled.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad (3)$$

3.3.5. F1 Score

The F1 Score determines their harmonic mean in an effort to achieve a balance between recall and precision. The maximum possible value for this precision measurement is 1. It implies perfect recall and precision.

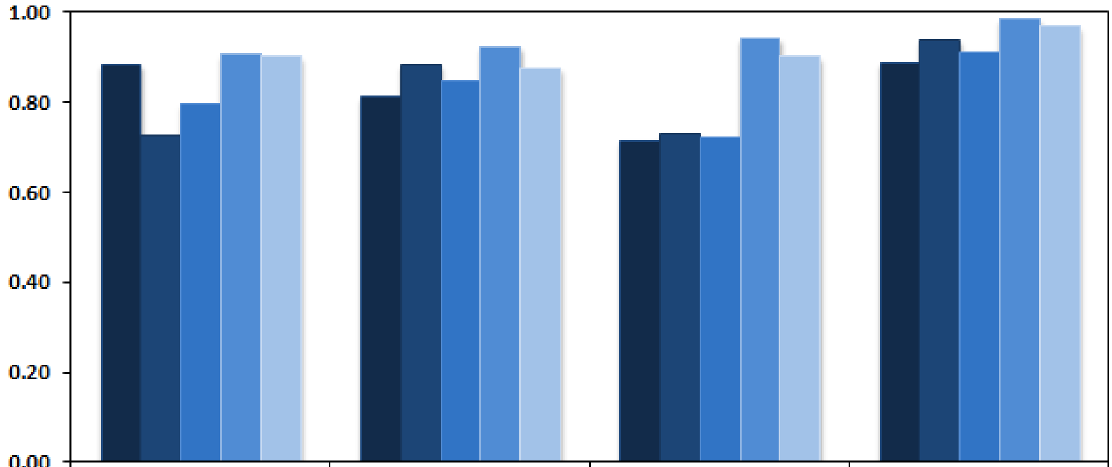
$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (4)$$

4. RESULTS AND DISCUSSIONS

In this section, we provide the findings and analyses of both techniques on the chest radiography: 1) Densenet121 Model 2) Vgg16 Model 3) ResNet152V2 Model and 4) Novo-NEX Model. We computed the F1-score, recall (sensitivity), and precision (positive predictive value) for each class on the test dataset to assess the performance of any model. We estimated the accuracy, the macro average, and the weighted average to assess the overall efficiency of every model. We plotted the confusion matrix to visualise the performance of various models.

4.1. Results of Pretrained Densenet121Model

Experiments with the pretrained Densenet121 model yielded the following results. Figure 4 displays the classification results for all classes in terms of recall, specificity, accuracy, and F1 score, whereas Figure 5 displays the confusion matrix to each classification. Densenet121 achieved 1) 82.50% overall test accuracy; 2) 0.73 precision, 90.21 percent accuracy, 0.80 F1-Score and 0.88 recall value for the Normal class classification; 3) 0.88 precision, 87.71 percent accuracy, 0.85 F1-Score and 0.81 recall for the Bacterial Pnemonia class classification; 4) 0.73 precision, 90.21 percent accuracy, 0.72 F1-Score and 0.72 recall for the Viral Pnemonia class classification; and 5) 0.94 precision, 96.86 percent accuracy, 0.91 F1-Score and 0.89 recall for the Covid-19 class classification.



	Normal	Baterial Pnemonia	Viral Pnemonia	COVID-19
Recall	0.88	0.81	0.72	0.89
Precision	0.73	0.88	0.73	0.94
F1 Score	0.80	0.85	0.72	0.91
Spceificity	0.91	0.92	0.94	0.99
Accuracy	90.21%	87.71%	90.21%	96.86%

Figure 4. Performance of the model on the Chest radiography test dataset using pre-trained DenseNet121

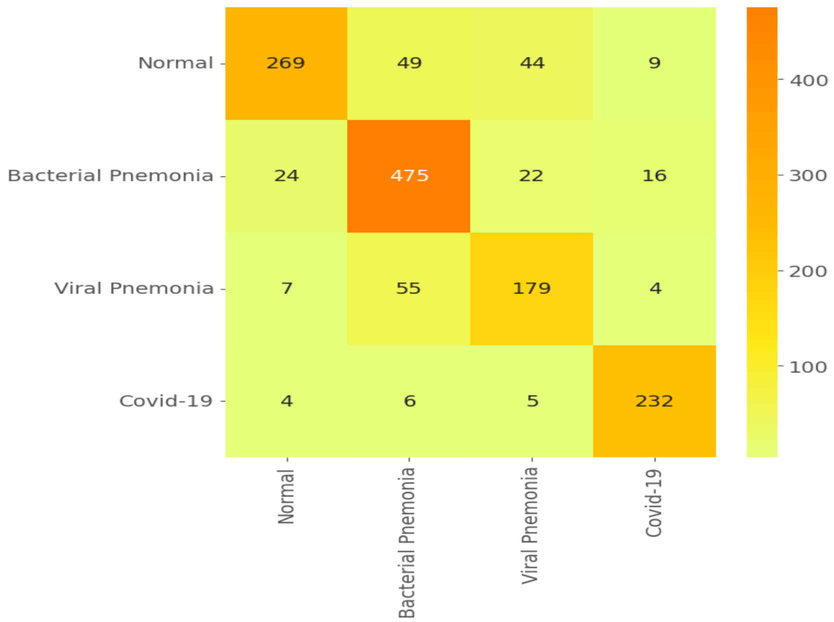


Figure 5. Confusion matrix of the model using pre-trained DenseNet201

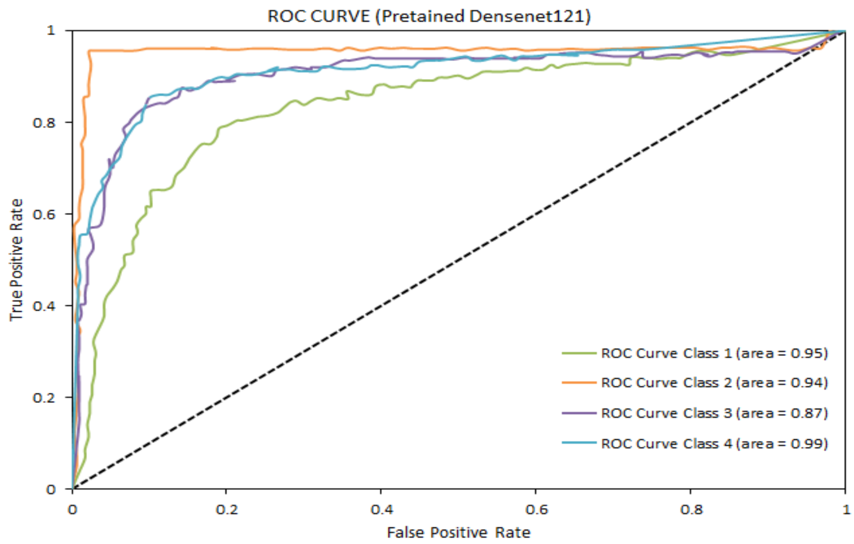
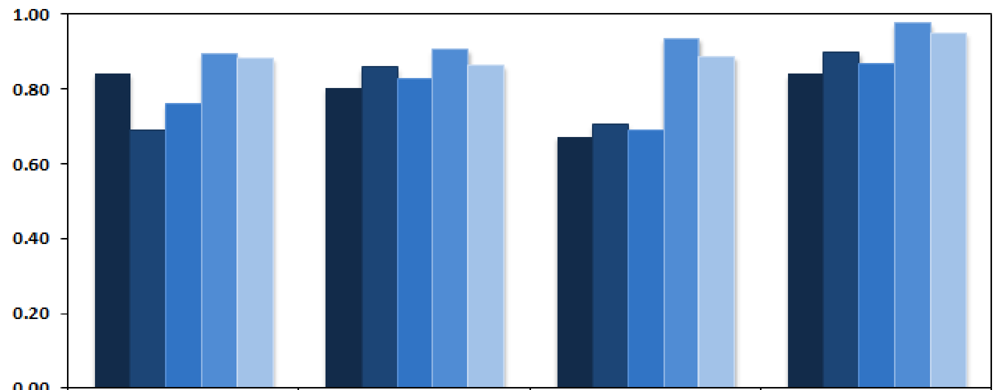


Figure 6. ROC Curve of the model using pre-trained DenseNet201

4.2. Results of Pretrained VGG16 Model

Experiments with the pretrained Densenet121 modelyielded the following results. Figure 7 displays the classification results for all classes in terms of recall, specificity, accuracy, and F1 score, whereas Figure 8 displays the confusion matrix to each classification. Densenet121 achieved 1) 79.5% overall test accuracy; 2) 0.69 precision, 88.43 percent accuracy, 0.76 F1-Score and 0.84 recall value for the Normal class classification; 3) 0.86 precision, 86.5 percent accuracy, 0.83 F1-Score and 0.80 recall for the Bacterial Pnemonia class classification; 4) 0.71 precision, 88.86 percent accuracy, 0.69 F1-Score and 0.67 recall for the Viral Pnemonia class classification; and 5) 0.90 precision, 95.21 percent accuracy, 0.87 F1-Score and 0.84 recall for the Covid-19 class classification.



	Normal	Baterial Pnemonia	Viral Pnemonia	COVID-19
Recall	0.84	0.80	0.67	0.84
Precision	0.69	0.86	0.71	0.90
F1 Score	0.76	0.83	0.69	0.87
Spceificity	0.90	0.91	0.94	0.98
Accuracy	88.43%	86.50%	88.86%	95.21%

Figure 7. Performance of the model on the Chest radiography test dataset using pre-trained VGG16

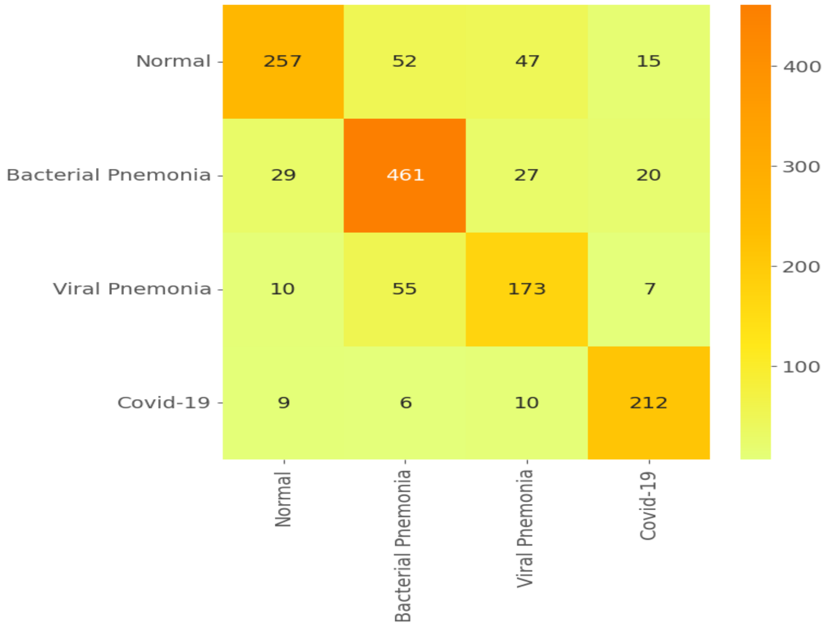


Figure 8 Confusion matrix of the model using pre-trained VGG16

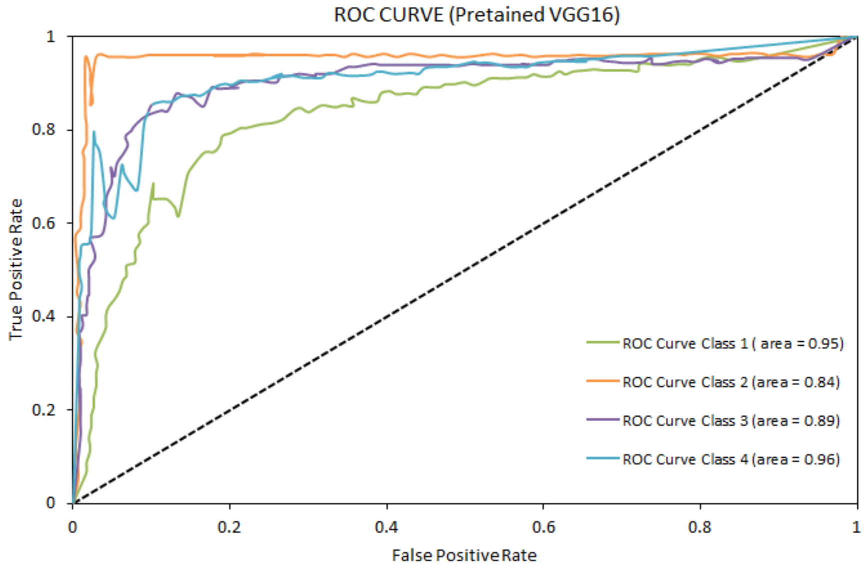
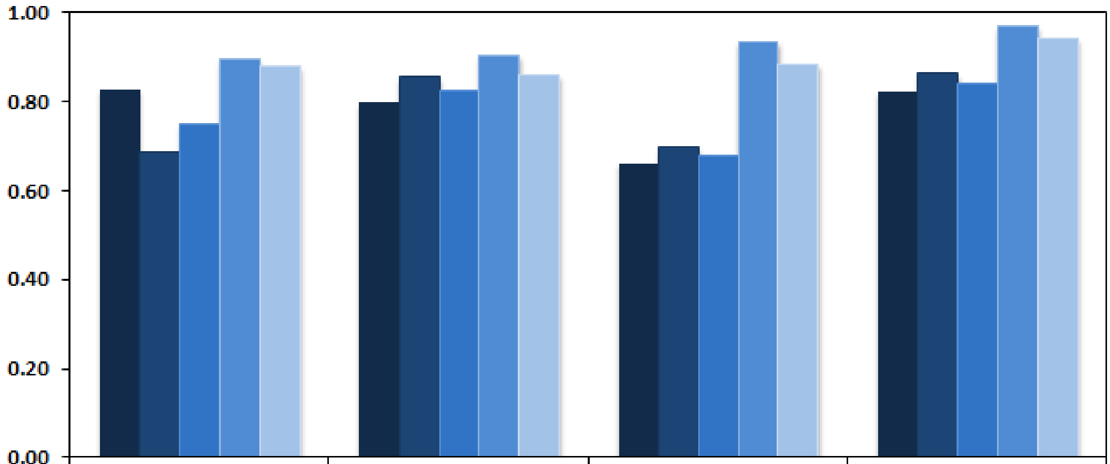


Figure 9 ROC Curve of the model using pre-trained VGG16

4.3. Results of Pretrained ReNet152V2 Model

Experiments with the pretrained Densenet121 model yielded the following results. Figure 10 displays the classification results for all classes in terms of recall, specificity, accuracy, and F1 score, whereas Figure 11 displays the confusion matrix to each classification. Densenet121 achieved 1) 78.43% overall test accuracy; 2) 0.69 precision, 87.93 percent accuracy, 0.75 F1-Score and 0.83 recall value for the Normal class classification; 3) 0.85 precision, 86.14 percent accuracy, 0.83 F1-Score and 0.80 recall for the Bacterial Pnemonia class classification; 4) 0.70 precision, 88.5 percent accuracy, 0.68

F1-Score and 0.66 recall for the Viral Pnemonia class classification; and 5) 0.86 precision, 94.29 percent accuracy, 0.84 F1-Score and 0.82 recall for the Covid-19 class classification.



	Normal	Baterial Pnemonia	Viral Pnemonia	COVID-19
Recall	0.83	0.80	0.66	0.82
Precision	0.69	0.85	0.70	0.86
F1 Score	0.75	0.83	0.68	0.84
Spceificity	0.89	0.91	0.94	0.97
Accuracy	87.93%	86.14%	88.50%	94.29%

Figure 10 Performance of the model on the Chest radiography test dataset using pre-trained ResNet152V2

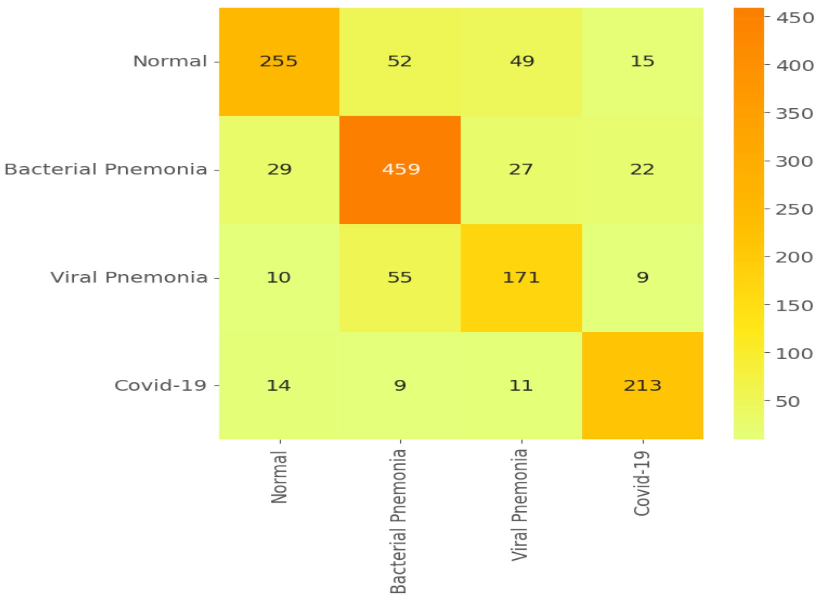


Figure 11 Confusion matrix of the model using pre-trained ResNet125V2

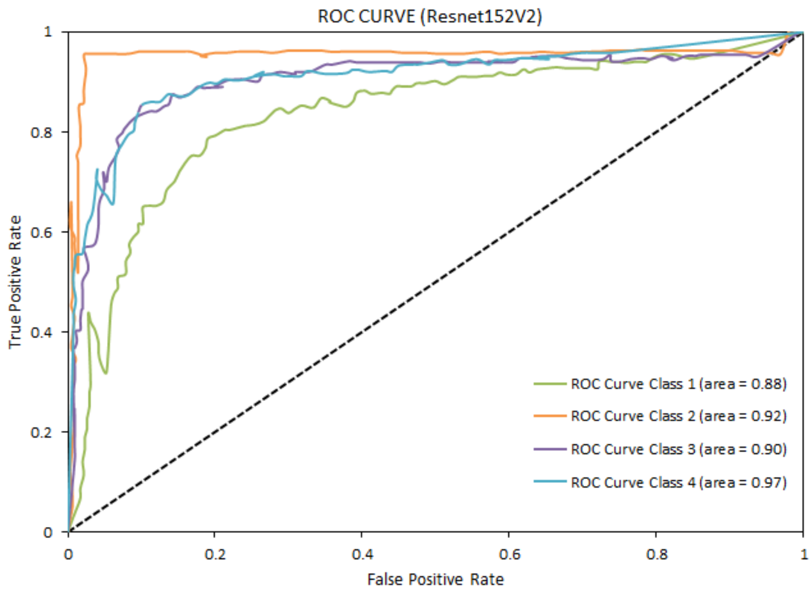


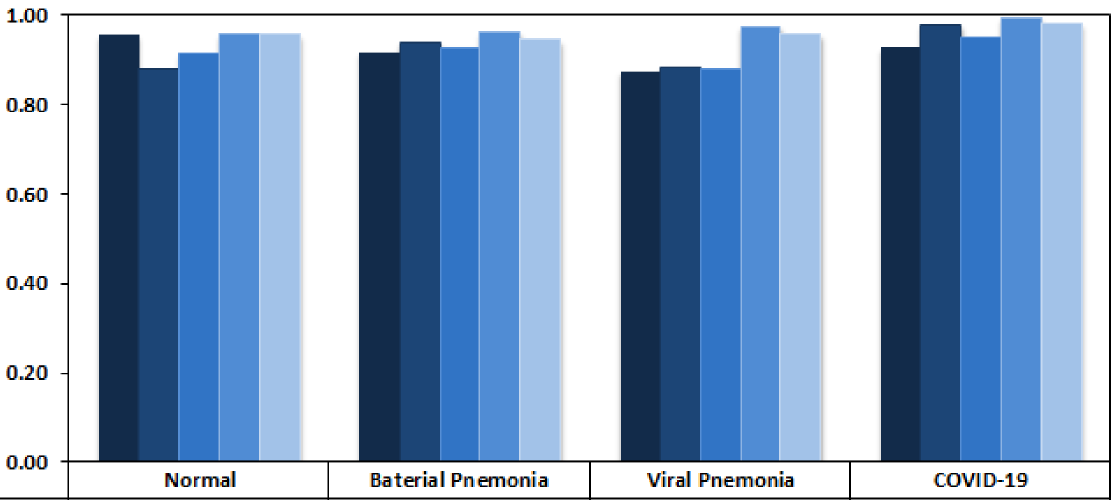
Figure 12 ROC Curve of the model using pre-trained ResNet152V2

4.4. Results of Novo-NEX Model

The propounded Novo-NEX model is fully trained on the chest radiography dataset and then Adam optimizer is used to further refine it. The chest radiography dataset's images are scaled to (256 x 256 x 3). Each image's pixel value is rescaled by a factor of 1./255. In our suggested model, the final prediction layer is activated by softmax activation, and all convolutional layers are activated by ReLU activation.

In this study, a manual search strategy is used to fine-tune the model's hyperparameters, which are displayed in Table 2. During training, we employed an initial learning rate of 0.001, 32 batch sizes and 200 epochs. We implemented an early stop and applied a 40% dropout to the dropout layer that comes after the global average pooling layer to reduce overfitting. During training, the categorical cross-entropy loss function improved for multi-class classification.

Experiments with the pretrained Novo-NEX model yielded the following results. Figure 13 displays the classification results for all classes in terms of recall, specificity, accuracy, and F1 score, whereas Figure 14 displays the confusion matrix to each classification. Densenet121 achieved 1) 92.14% overall test accuracy; 2) 0.88 precision, 95.71 percent accuracy, 0.92 F1-Score and 0.96 recall value for the Normal class classification; 3) 0.94 precision, 94.5 percent accuracy, 0.93 F1-Score and 0.92 recall for the Bacterial Pnemonia class classification; 4) 0.89 precision, 95.79 percent accuracy, 0.88 F1-Score and 0.88 recall for the Viral Pnemonia class classification; and 5) 0.98 precision, 98.29 percent accuracy, 0.95 F1-Score and 0.93 recall for the Covid-19 class classification.



	Normal	Baterial Pnemonia	Viral Pnemonia	COVID-19
Recall	0.96	0.92	0.88	0.93
Precision	0.88	0.94	0.89	0.98
F1 Score	0.92	0.93	0.88	0.95
Spceificity	0.96	0.96	0.98	1.00
Accuracy	95.71%	94.50%	95.79%	98.29%

Figure13 Performance of the model on the Chest radiography test dataset using Novo-NEX

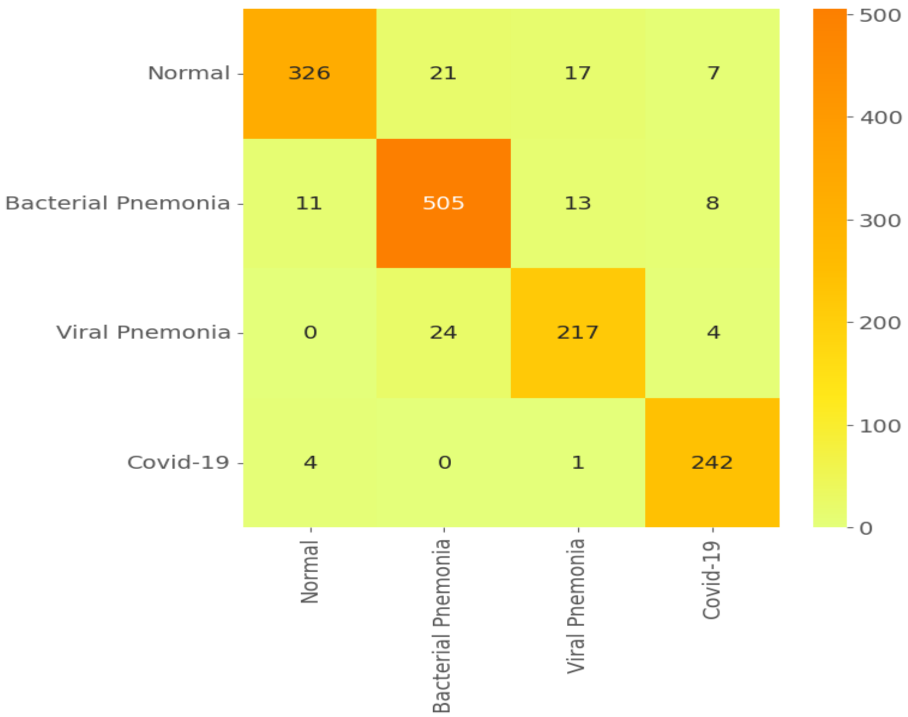


Figure 14 Confusion matrix of the model using Novo-NEX

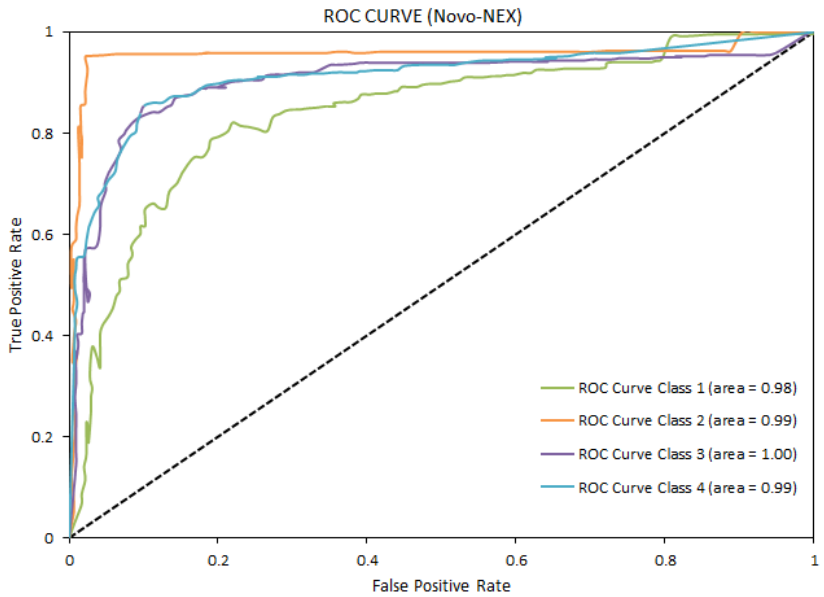


Figure 15 ROC Curve of the model using pre-trained Novo-NEX

4.5. Comparison of Novo-NEX model with the pretrained models

It can be seen from the results (Refer Table 1) that the performance of the Novo-NEX is always better than that of other pre-trained models. During experimentation, it is found that pre-trained DenseNet121 model outperformed other pre-trained CNNs. Hence, in case if the dataset is small, pre-trained DenseNet121 model can be used instead of other pre-trained models.

Table 1 Comparision of Novo-NEX Model with the pretrained models

	Category	**Recall**	**Precision**	**F1 Score**	**Specificity**	**Accuracy**	**Overall Accuracy**
DenseNet121	Normal	0.88	0.73	0.80	0.91	90.21%	**82.50%**
	Bacterial Pneumonia	0.81	0.88	0.85	0.92	87.71%	
	Viral Pneumonia	0.72	0.73	0.72	0.94	90.21%	
	Covid-19	0.89	0.94	0.91	0.99	96.86%	
VGG16	Normal	0.84	0.69	0.76	0.90	88.43%	**79.50%**
	Bacterial Pneumonia	0.80	0.86	0.83	0.91	86.50%	
	Viral Pneumonia	0.67	0.71	0.69	0.94	88.86%	
	Covid-19	0.84	0.90	0.87	0.98	95.21%	
ResNet152V2	Normal	0.83	0.69	0.75	0.89	87.93%	**78.43%**
	Bacterial Pneumonia	0.80	0.85	0.83	0.91	86.14%	
	Viral Pneumonia	0.66	0.70	0.68	0.94	88.50%	

	Covid-19	0.82	0.86	0.84	0.97	94.29%	
Novo-NEX	Normal	0.96	0.88	0.92	0.96	95.71%	**92.14%**
	Bacterial Pneumonia	0.92	0.94	0.93	0.96	94.50%	
	Viral Pneumonia	0.88	0.89	0.88	0.98	95.79%	
	Covid-19	0.93	0.98	0.95	1.00	98.29%	

5. CONCLUSIONS

The trained Novo-NEX model proposed in this research study for the COVID-19 detection and pneumonia detection on chest x-ray images have meaningful results. The developed Novo-NEX model was effective in extracting features from an x-ray image and forecast the occurrence or nonexistence of COVID-19, bacterial, and viral-pneumonia. Likewise, testing-data in the research was intensified through data augmentation techniques. In addition to the improvement of computer-related applications in the medical division, COVID-19 and pneumonia can be efficiently found employing chest radiographs with the support of CNN and deep learning technologies. Methodologies developed in the conduct of this research in which COVID-19, bacterial, and viral-pneumonia can be forecast with greater accuracy, and in this case our study obtained 92% accuracy. The medical field through automated diagnosis is the essential area that will gain precisely from this research. Future studies can make better a performance of CNN architecture by tuning the hyper-parameters and transfer learning combinations. Improved complex network-structure might likewise achievable to determine the best model for pneumonia and the COVID-19 detection system.

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