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Research Article

Application with deep learning models for COVID-19 diagnosis

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Abstract

COVID-19 is a deadly virus that first appeared in late 2019 and spread rapidly around the world. Understanding and classifying computed tomography images (CT) is extremely important for the diagnosis of COVID-19. Many case classification studies face many problems, especially unbalanced and insufficient data. For this reason, deep learning methods have a great importance for the diagnosis of COVID-19. Therefore, we had the opportunity to study the architectures of NasNet-Mobile, DenseNet and Nasnet-Mobile+DenseNet with the dataset we have merged. The dataset is divided into three separate classes: Normal, COVID-19, and Pneumonia. Recall, Precision, and F-measure are the main metrics which used to measure the performance of classification algorithms. The accuracy is obtained as 87.16%, 93.38% and 93.72% for the NasNet-Mobile, DenseNet and NasNet-Mobile+DenseNet architectures for the classification, respectively. The results once again demonstrate the importance of Deep Learning methods for the diagnosis of COVID-19.

Keywords: COVID-19 diagnosis, DenseNet, NasNet-Mobile, deep learning classification

1. Introduction

Coronavirus disease (COVID-19), which emerged toward the end of the 2019, is a type of coronavirus known to infect extremely rapidly. The International Committee on Virus Taxonomy has named this virus SARS-COV-2 [1,2].

In cases where coronavirus is not diagnosed and treated quickly, a severe clinical picture can be observed, which can lead to pneumonia and death [3,4]. In addition, the continuous emergence of different variants affects the diagnosis and treatment process negatively. At this point, imaging examination, as a rapid and more convenient examination [5] method, plays a role in reducing the cost of disease worldwide as well as significantly shortening the time for treatment of patients infected with COVID-19 [6,7].

Currently, radiographs and computed tomography (CT) are the main screening methods for diagnosis of COVID-19. These methods can contribute the very rapid screening of an infected person [8].

Recently, Deep Learning applications have become a highly accepted method in the field of image processing for diagnosing many types of diseases [9]. Since the emergence of COVID-19 virus, many researchers have developed Deep Learning based models for the detection of COVID -19 on radiological images and achieved successful results. Therefore, a study is conducted using Deep Learning models for rapid diagnosis of COVID-19. The dataset used in this study consists of three classes. Figure 1 shows the images of these classes.

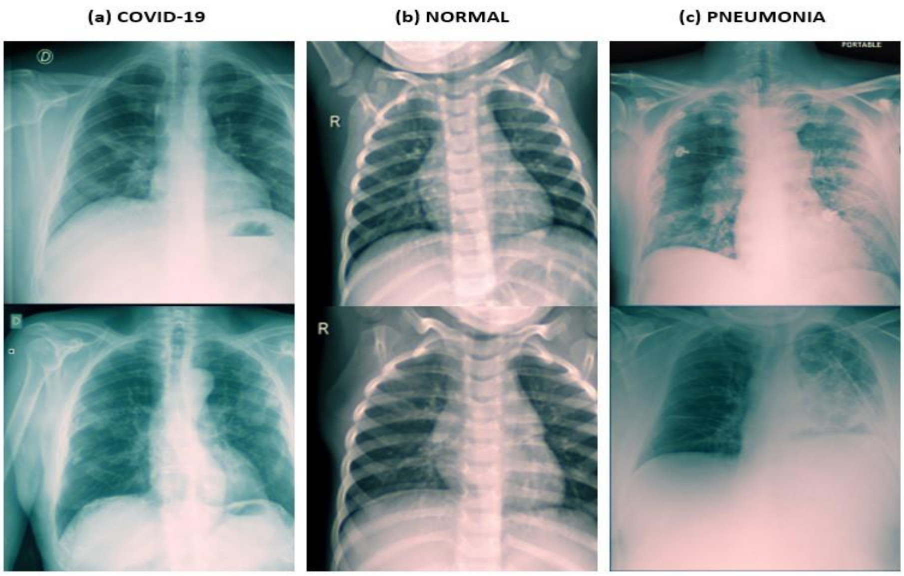

Figure 1 Sample images of COVID-19, Normal and Pneumonia

The main benefits of the study can be explained as follows:

- A balanced dataset is created with three separate class labels from the existing datasets. The dataset is beneficial and reliable for COVID-19 multi-classification problems.
- There was an opportunity to run DenseNet and NasNet-Mobile architectures separately and together on this dataset and examine the results.
- These architectural structures provide a highly accurate framework for the multi-classification problem through the radiographs and can be easily tested in hospitals with a computerized interface.

In the remainder of the paper, a literature review is conducted in the second part. Material and methods are presented in chapter 3, research results and discussion are explained in chapter 4, finally, conclusion is given in chapter 5.

2. Related Works

If examining the literature on COVID-19 classification and diagnostic methods, the first thing that stands out is the study conducted by Jia et al. using the dynamic CNN model. In this study, they found that the understanding and classification of Chest X-Ray, Computed Tomography (CT) scans are of great importance in the diagnosis of COVID-19. Existing researches on classification of COVID-19 cases are due to instability of data, insufficient generalizability, lack of studies, etc. They said they faced difficulties. To solve these problems, their study proposed a kind of modified MobileNet to classificate COVID-19 X-ray images. A later ResNet block for CT image classification and CNN modification method, they made a design that can improve the performance for solving the problem and classification. The proposed methods obtain a test accuracy of 99.6% for the CXR image dataset with five categories and a test accuracy of 99.3% for the CT image dataset [10].

Fang and Wang conducted a study on a convolution-based COVID-19 deep learning classification architecture and the local evolution of deconvolution. In this study, they stated that COVID-19 is a strain that makes a significant difference between normal patients with asymptomatic infections and patients with coronavirus or pneumonia. In order to effectively improve the accuracy of normal and COVID-19 assessment by manual examination by doctors, this paper proposed a deep learning model based on improving the current situation. Additionally, this paper was prepared using an open access COVID-CT dataset of 143 novel coronaviruses provided by Petuum researchers at the University of California, San Diego. The dataset (original image, organized image) contains 1460 images. For the performance of the model, 70% of this dataset was used for the train and the remaining one was used for testing. It has been shown that the proposed network has high classification success. The corresponding values for sensitivity, specificity, and precision are %98, %96, %98, respectively [5].

Singh et. al developed a machine learning model to classify images with or without COVID-19. In this study, they presented an alignment-free approximation model to classify COVID-19. The dataset used here consists of a total of 1582 image samples with genome sequences of different lengths from different area obtained from different data and divided into COVID-19 and non-COVID-19 groups. The avaliable dataset dataset was used to test the accuracy and performance of the F-measure-based classifiers by 10-fold cross-validation. In addition, a cross-validation tests with paired "t" tests were used to test the best model with unused dataset. The random forest method was identified as the best model to discriminate COVID-19. It also formed a control group with 97.4% of accuracy, 96.2% of sensitivity and 98.2% of specificity when tested with unknown samples [11].

Gour and Jain performed a study on classification of images with uncertain convolutional networks for COVID-19 radiographs. In this study, they mentioned that deep learning methods were successful during image process analysis detection. They also designed an uncertainty sensitive deep learning model called UA-ConvNet for automatic detection of COVID-19 diseases from Chest X-Ray images. The method they developed was evaluated on three datasets consist of chest x-ray data, COVID-19 x-ray data and Kaggle-based datasets. The UA-ConvNet architecture achieved a G average of 98.02% and a precision of 98.15% for the classification mission on the COVID-19 X-ray dataset. The proposed binary classification model achieved a G-mean of 99.16% and a precision of 99.30% for the radiograph dataset [12].

Hassan et al. conducted a study to review and classify COVID-19 CT imaging models. In their study, they proposed a joint AI-based model for the diagnosis of the COVID-19 model and CT images. After reviewing previous studies, they argued that the COVID-19 literature studies on computer image processing tasks such as classification and segmentation were insufficient. Therefore, studies on COVID-19 deep learning methods based on CT images focused on. They preferred to scan popular websites such as Kaggle, GitHub, Google Scholar, , IEEE Xplore and ScienceDirect in order to align related studies. After extensive research, 114 studies were reviewed and selected research analyzes suggested that artificial intelligence and computer vision have significant potential for rapid COVID-19 virus diagnosis as they can contribute significantly to the automation of the diagnostic process. In addition, they concluded in the study that deep learning methods are extremely important for the diagnosis of COVID-19 [13].

Tuncer et al. presented a new method for classifying covid-19 and pneumonia called "F-transformation". In this study, they stated that COVID-19 is an important disease affecting life all over the world. Since COVID-19 disease is similar to pneumonia, three classes of datasets were used in their study: COVID-19, pneumonia, and normal lung radiographs. Using this dataset, a new machine learning model, called the example model, is presented. First, a fuzzy tree transform was applied to each box image used, and 15 images were obtained from a box image. In the continuation of the study, the pattern splitting process was applied to the existing images. Valuable features were then selected through the iterative neighborhood component (INCA). INCA selects the 616 most prominent features and these features are output to the 16 different classifiers. The best classifier is the cubic support vector machine, which provides a classification accuracy of 97.01% for this dataset [14].

Balaha et al. proposed a Deep Learning-based hybrid system for segmentation of COVID-19 virus. The study proposes a hybrid COVID-19 architecture based on deep learning. In the segmentation phase was proposed using X-ray images to extract the lungs. For the classification phase, a hybrid CNN with an abstract designed CNN model was used. Using the model, which they named HMB-HCF, they achieved a successful result with 99.84% of accuracy [15].

Islam and Nahiduzzaman conducted a study on complex feature extraction for COVID19 detection from CT scan images using a machine learning approach based on the ensemble model. In this study, they tried the Contrast Limited Histogram Equalization method to CT images as a pre-processing step to improve the images. Finally, they developed a new CNN model to extract 100 salient features from a total of 2482 CT s images. This ensemble model achieved 99.73%, 99.46%, and 100% accuracy, precision and recall, respectively [16].

3. Material and Methods

In this paper, DenseNet and NasNet-Mobile networks have separated and operated together to show the superiority of the hybrid models.

The block diagram containing the process steps of the applied work is shown in Figure 2.

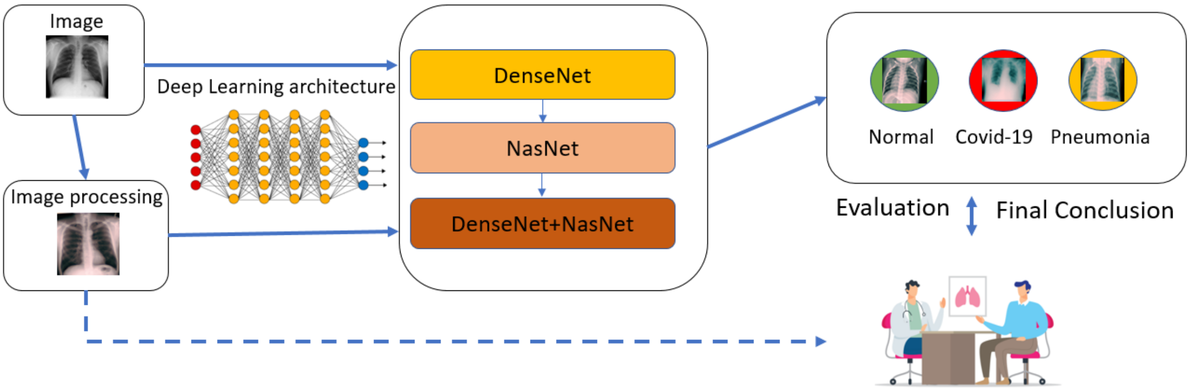

Figure 2 Block diagram of the proposed model

3.1 DenseNet Network Structure

In Figure 3, the architectural structure of DenseNet is explained in a simple way.

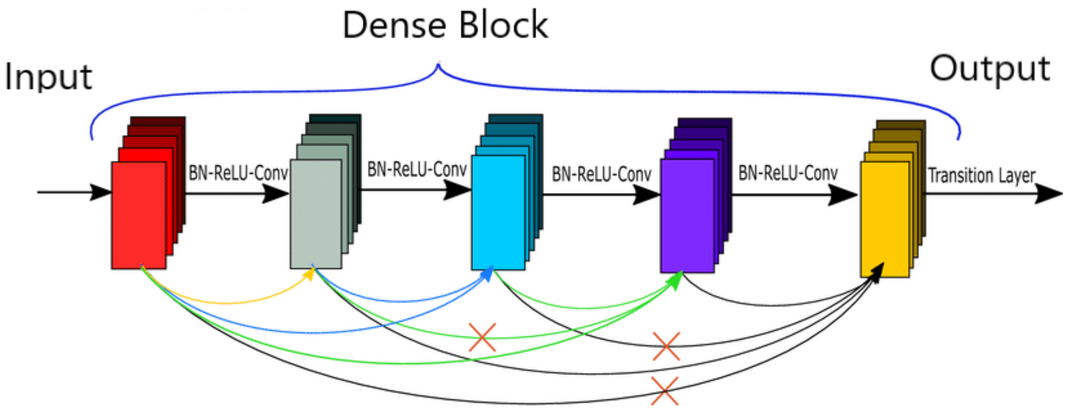

Figure 3 DenseNet Architecture

The neural network model of DenseNet differs from other convolutional neural networks by two basic features. The first feature is the dense connection layer structure. In this structure, the layers are linked to each of the previous layers to allow for feature reuse. Second, due to feature reuse, each layer uses a small number of convolutional kernel subtraction features to reduce redundancy. For this reason, in DenseNet, layers are merged with all previous layers in channel size. The advantages of DenseNet are mainly the following:

- Effective solution to the problem of the disappearance of the gradient
- Propagation of the support feature
- Reuse of the support feature
- Significant reduction of the number of parameters

This model can bypass the pre-training on Image Net dataset and achieve the goal of time saving and efficiency by starting the training directly with the randomly initiated model. In many large-scale studies, there may be significant differences when comparing the actual dataset to the ImageNet dataset. Therefore, it may be a rational alternative to apply the model that does not require prior training in imaging studies [17,18].

3.2 NasNet-Mobile Network structure

The NasNet-Mobile architectural structure is shown in Figure 4.

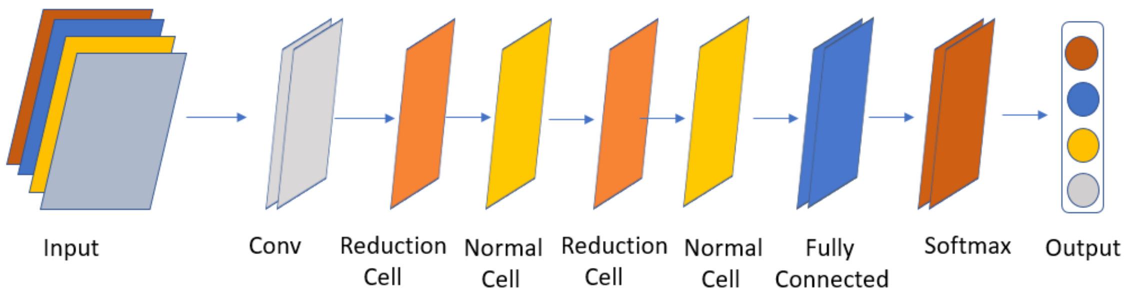

Figure 4 NasNet-Mobile Architecture

NasNet-Mobile Convolutional Neural Network is trained from ImageNet dataset. The network has succeeded in recognizing images using an active feature. The size of the input images is 224*224. NasNet architecture is basically divided into two classes, NasNetMobile and NasNetLarge. The NasNetMobile network is designed for smaller datasets compared to NasNetLarge. It uses the search strategy to search for layers or cells with the best convolutions in relatively small image datasets. Convolutional cells are used to achieve better classification performance and a smaller computational budget. In NasNet, although the architecture is predetermined, the number of cells or blocks to be found by the search method, that is, the number of initial convolution filters, are free parameters. [19].

3.3 DenseNet+NasNet-Mobile Architectural Structure

The layered structures, parameter numbers, and combination values of the model created by combining the architectural structures of DenseNet+NasNet-Mobile were arranged. The architectural design was created by starting with the DenseNet block in the input layer and then adding the NasNet-Mobile block. It starts with the input image size (224,224.3) and changes to (7,7,1024) in the concatenation phase. Then, in the output layer, it is converted to the last convolutional block structure of size (7,7,32). Finally, the model structure is completed by smoothing the output layer with three classes using the softmax function.

3.4 Image Pre-processing

Image pre-processing is required in Deep Learning architectures, especially when the dataset is difficult to interpret. At this stage, image pre-processing techniques are used to better explore and interpret existing images. In this study, a series of pre-processing steps are performed using the OpenCV library in Python. First, its value is set to 255 (white) if the pixel density is greater than the specified threshold, and 0 (black) otherwise. Then a noise removal technique is used to keep the edges sharp. Finally, the contrast of the image is increased to expand the intensity range. Figure 5 shows the images before and after image pre-processing.

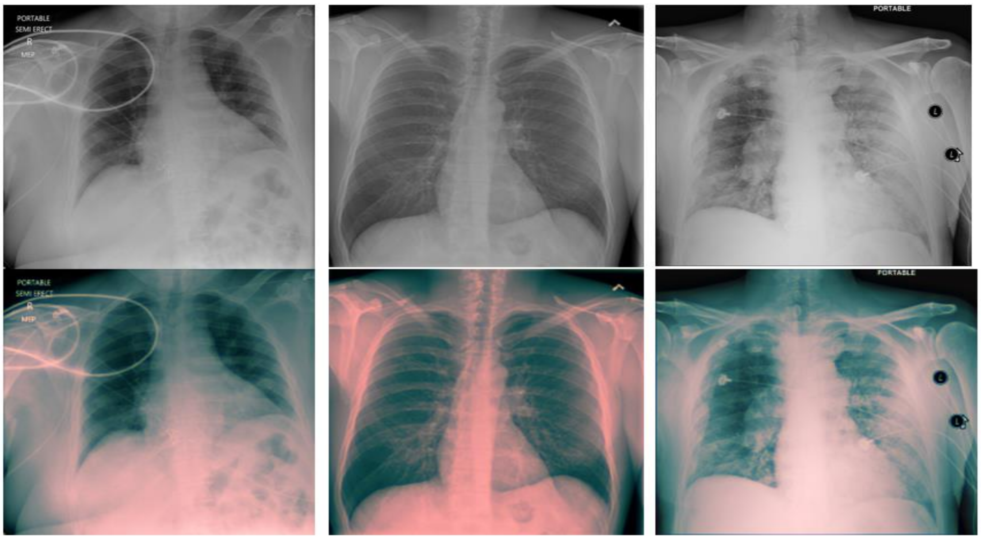

Figure 5 Image pre-processing phase

3.5 Dataset

Explanations about the dataset and all labels can be downloaded from the relevant link(for dataset: https://github.com/turkfuat/covid19-multiclass). In the study, three different datasets were examined in details. The images in the dataset belong to three different classes:

- Normal: individuals without signs of disease on their chest images.
- COVID -19: Individuals diagnosed by physicians who show the spread of COVID -19 virus on their chest images.
- Pneumonia: Includes individuals who show pneumonia (with subtypes) on chest images and have been diagnosed by physicians.

Firstly, the images in the data set from Deb et al [20] were analyzed and transferred to the data pool. Then the images in the dataset from COVID-19 Grand Challenge were added to this pool with the same labels. Finally, different data with the same labels from the dataset from Cohen et al [21] were imported into data warehouse. The current state of the dataset is shown in Table 1.

Table 1 Merged and Balanced Dataset

	Normal	**COVID-19**	**Pneumonia**
Train	7834	8107	7025
Valid	1679	1737	1505
Test	1679	1738	1506
Total	11192	11582	10036

3.6 Performance Evaluation Criteria

Accuracy, Sensitivity, Precision and F1-score are the main metrics for measure the performance of the classification algorithms. Accuracy shows the ratio of correct prediction rate. It is calculated as:

$$Accuracy = (TN + TP)/(TP + FP + TN + FN) \tag{1}$$

Precision shows how many of the values predicted as Positive are actually relevant. Precision value is calculated as:

$$Precision = TP / (TP + FP) \tag{2}$$

Sensitivity is a true positive rate that expresses the probability of a positive test provided it is actually positive. Sensitivity value is calculated as:

$$Sensitivity = TP/(TP + FN) \tag{3}$$

F1-Score takes into account both precision and sensitivity as harmonic mean. It is calculated as:

$$F1 - Score = 2 * (Recall * Precision) / (Recall + Precision) \tag{4}$$

Furthermore, the precision, sensitivity and F1-Score values for three models are shown in Table 3.

4. Results and Discussion

The training and testing process is performed on the GTX 1070 TI graphics card for about two hours. The Adam optimizer is used for the model followed by the Leaky Relu activation function.

The learning rate is set as 0.0001 and the stack size as 32. The accuracy values of the three models run at 100 steps are shown in Table 2. It is found that the accuracy value increased to 93.72% with image pre-processing and using both models together.

Table 2 Accuracy Values of The Models

Model name	Accuracy (%)
DenseNet	93.38
NasNet-Mobile	87.16
Dense Net+ NasNet-Mobile	92.46
Dense Net+ NasNet-Mobile (with image pre-processing)	93.72

In Figure 6, the accuracy and loss values for Nasnet mobile are shown, and in Figure 7, the accuracy and loss values for the DenseNet architecture are shown. Figure 8 shows the accuracy and loss values obtained by using both models in combination.

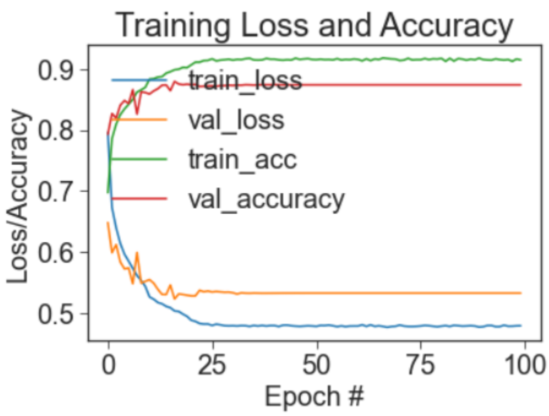

Figure 6 Accuracy/Loss Values for Nasnet-Mobile Model

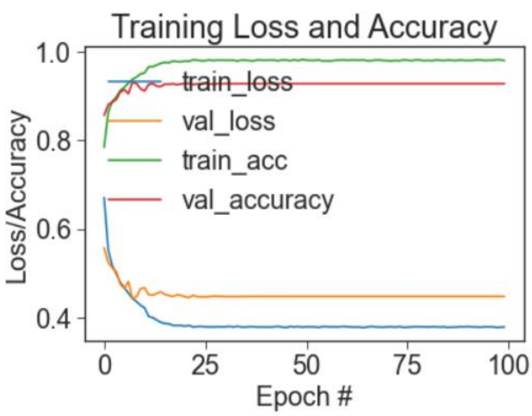

Figure 7 Accuracy/Loss for DenseNet Model

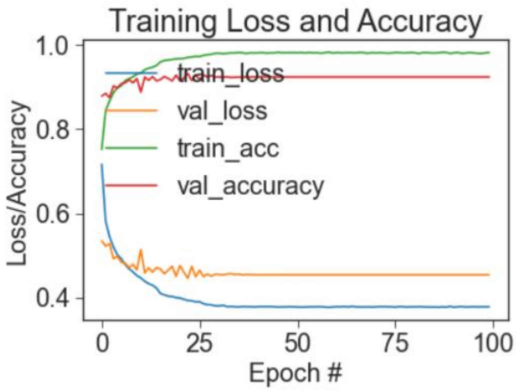

Figure 8 Accuracy/Loss for NasNet-Mobile+DenseNet Model

Table 3 shows the accuracy, recall, and F1 score values for all three models. When the results are compared, it is clear that the DenseNet+NasNet-Mobile model gives more successful results.

Table 3 Precision/Sensitivity/F1-Score values for three models

Class	**Accuracy**	**Precision**	**Sensitivity**	**F1-Score**	**Test Samples**
	NasNet-Mobile				
COVID-19	0.87	0.87	0.87	0.87	1738
Normal	0.86	0.89	0.86	0.88	1679
Pneumonia	0.88	0.86	0.88	0.87	1506
	DenseNet				
COVID-19	0.91	0.97	0.91	0.94	1738
Normal	0.94	0.91	0.94	0.93	1679
Pneumonia	0.95	0.92	0.95	0.93	1506
	DenseNet+ NasNet-Mobile				
COVID-19	0.91	0.97	0.91	0.94	1738
Normal	0.96	0.92	0.96	0.94	1679
Pneumonia	0.94	0.93	0.94	0.94	1506

In Figure 9, the values of the confusion matrix for Nasnet mobile are shown. In Figure 10, the values of the confusion matrix for the DenseNet architecture are shown. Figure 11 shows the confusion matrix results from using both models together.

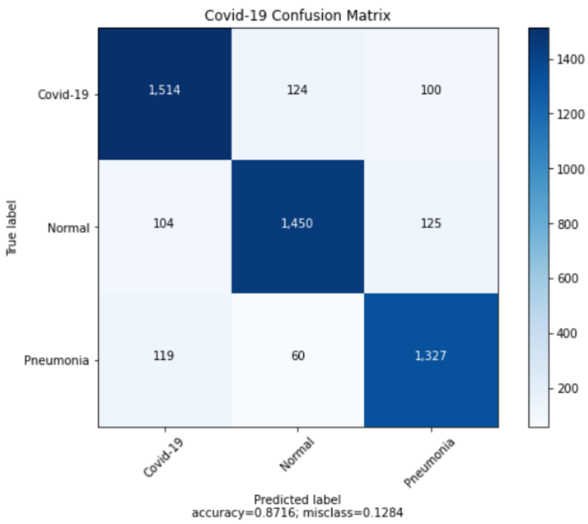

Figure 9 Confusion Matrix for NasNet-Mobile

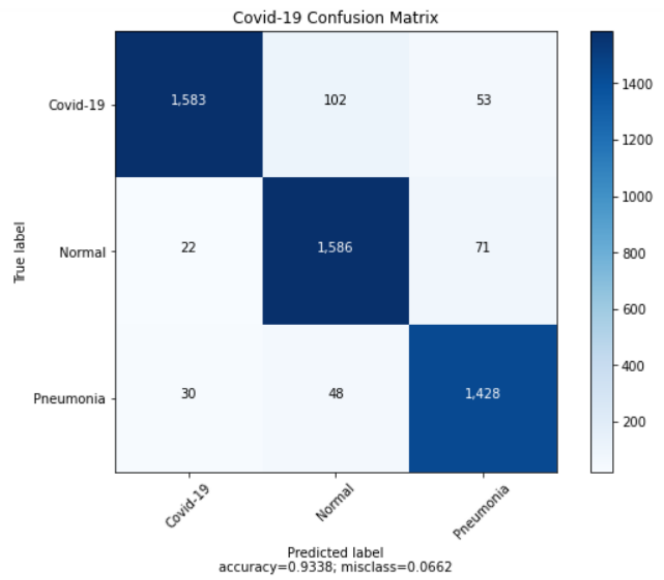

Figure 10 Confusion Matrix for DenseNet

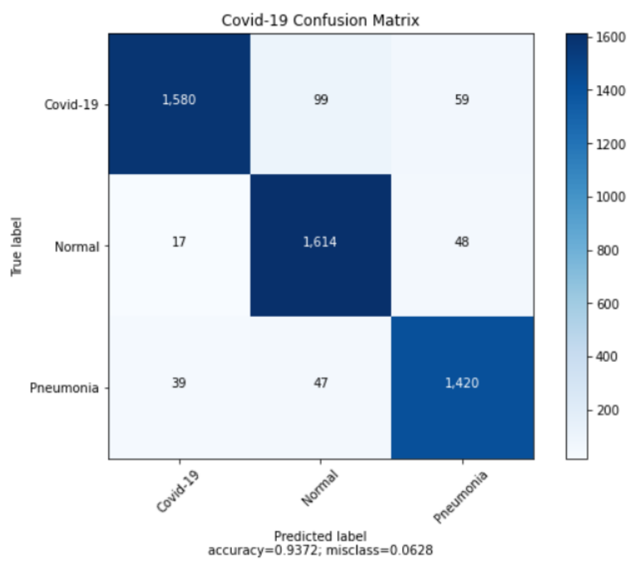

Figure 11 Confusion Matrix for NasNet-Mobile+DenseNet

Figure 12 lists some examples of images that were mislabeled as a result of the testing process of all three models. When the incorrectly labeled results are examined, it is noteworthy that the classes of COVID-19 and pneumonia are often confused.

True:	COVID-19	COVID-19	NORMAL	Pneumonia	Pneumonia
Predict:	Pneumonia	Pneumonia	Pneumonia	COVID-19	COVID-19

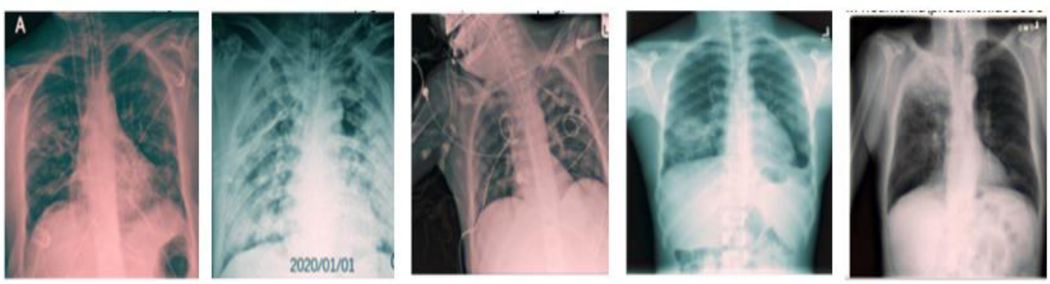

Figure 12 Some images that were mislabeled as a test result

Table 4 shows an overall comparison of the results of other studies in the literature with the results of this study. According to table, MAI-Net architecture was the study that gave the most successful results. It is seen that the developed model gives respectable results when compared with the studies on similar data sets. In addition, it can be said that subclass types are also important in multi-class studies. Even small differences in CT images can lead to incorrect results in classification. Given these details, it can be said that the DenseNet+NasNet-Mobile model has had remarkable success in classification problems.

Table 4 Comparison of the model with the similar studies

Study	Dataset	Architecture	Accuracy (%)
Wang et al. [22]	https://github.com/lindawangg/COVID-Net	Covid-Net	92.4
Lascu [23]	Kaggle Dataset	FC-DenseNet	-
Wang et al [24]	covid-chestxray-dataset	MAI-Net	96.42
Wang et al [25]	covid-chestxray-dataset	CFW-Net	94.35
Asif et. al. [26]	Cohen et al.	Xception	89.6
Ozturk et al. [27]	Cohen et al.	Darknet	87.02
Ioannis et al. [28]	Kaggle Challenge Dataset	VGG19	93.48
Deb et al. [20]	Private Dataset	Ensemble M.	91.39
Rahimzadeh et. al [29]	Covid-chestxray-dataset + Kaggle Challenge Dataset	Xcept- ResNet	91.4
Mahmud et al [30]	Private Dataset	CovXNet	89.6
DenseNet+NasNet	**Merged+Balanced**	**Ensemble M.**	**92.46**
DenseNet+NasNet (with image pre-processing)	**Merged+Balanced**	**Ensemble M.**	**93.72**

This method can primarily guide new users in deep learning applications where the data distribution is balanced but the classification task is difficult. It is clearly seen how the performance measures change when different architectural models are used separately or together. When NasNet-Mobile and DenseNet architectures are used together, it is seen that the accuracy rate reaches 93.72%. The disadvantage of the system is that it needs more time for classification.

Despite this, it can be said that the number of data is more and it is open to experimentation and development in different multi-class applications.

5. Conclusion

This research has enabled the application of deep learning models for the diagnosis of COVID-19 with chest radiographs. It also provides the opportunity to show the differences between COVID-19 and pneumonia images. The success of deep learning models in classification problems can be tested when models run together and separately. In addition, the newly created classes provide users with the ability to use the balanced dataset for COVID-19 classification studies. Three separate models we have developed have shown that Deep Learning methods can be successfully used in COVID-19 studies. We are optimistic that we can achieve even better results.

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