Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 06 Issue 02
2024

Research Article
https://doi.org/10.56979/602/2024

Diagnose of COVID-19 by Using CNN Based Models on Medical Images

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Received: May 21, 2023 **Accepted:** August 16, 2023 **Published:** March 01, 2024

Abstract: COVID-19 is a fast-spreading viral disease that affects both animals and people. Chest computed tomography and chest radiography are superior imaging techniques for detecting lung problems. This work was done to diagnose the COVID-19 disease by using CNN-based models on chest gray scale CT scan images. In the current study, the poster anterior view of the chest CT scan images has been used for both healthy subjects and patients with COVID-19 illness. Using the deep learning on CNN based models; we compared the performance of cleaned as well as augmented models. We have contrasted and compared precision of the Inception V3, Xception, and ResNeXt models. The dataset was generated from the Kaggle repository; there were 15102 gray scale chest CT scan pictures in the collected data set, including normal, COVID, and pneumonia. Total data set is further divided into training and validation sets. The Xception model detects images of chest CT scan with an accuracy of 98.90%, which is higher than state of the art approaches. This study makes medical claims and examines different classification schemes for patients infected with COVID-19.

Keywords: CT scan; CNN; Covid-19; Inception V3; ResNeXt; XCeption.

1. Introduction

The lethal disease known as COVID-19 is responsible for numerous deaths each day. This disease, which is caused by a virus and affects more than one country, has affected the entire globe. In the past ten years, numerous additional viruses, such as SARS, MERS, the flu, etc., have developed, but they only survive for a few days to months [1-3]. Due to the availability of vaccinations caused by these viruses, despite the fact that many scientists are researching them, relatively few of them, i.e., scientists or researchers, are diagnosing them. Today, COVID-19 disease affects the entire globe, and the most important truth is that no nation's scientists have been able to develop a vaccine to treat the disease. While numerous new hypotheses, such as plasma therapy and CT scan images, have entered the picture, the correct treatment for this lethal disease has yet to be identified. Daily deaths are attributed to COVID-19, and its diagnosis is extraordinarily costly for a nation, a state, and its victims [4-7].

In March 2020, a variety of online sources, including Github and Kaggle, made CT scan images of the healthy individuals as well as the COVID-19-infected individuals that were used for the analysis. Coronavirus-19 is a pandemic disease that has begun to threaten the global population. It is vital to differentiate between healthy individuals and people infected with COVID-19. To reduce the risk to patients who are not infected with COVID-19, the diagnosis of Covid-19 diseased people must be conducted with increased caution and under extremely strict standards [8, 9].

Individuals with the novel coronavirus infection initially developed a throat illness, followed by respiratory difficulties. Nobody is able to combat the COVID-19 disease, which is a hidden adversary. To protect the health of others, patients infected with COVID-19 must be isolated and undergo proper screening and preventive procedures [10, 11]. Once a person makes contact with a COVID-19-infected individual, this virus spreads via a chain mechanism. This epidemic requires the aid of hospital personnel, nurses, physicians, and clinical facilities in order to be identified. Many more approaches have reduced the influence of the COVID-19 infection. Medical imaging is another way to assess and predict the COVID-19 effects on the human body [12-14].

In current study, CT scan images of the healthy persons as well as those infected with COVID-19 were collected and uploaded to different sources. After that, we used three distinctive models to analyze COVID-19 (InceptionV3, Xception, and ResNeXt). The acquired data is processed using CNN, a technique for machine learning. This study is primarily concerned with classifying CT scan pictures for patients with coronavirus infections using CNN models. We have made an effort to make comparisons to prior work in the field and to explore potential task models that can be investigated further to demonstrate their utility in real-world settings. This study examines the influence of the COVID-19 infection on nations as well as individuals [15].

2. Related Work

In 2020, CT scan images were used by scientists who projected a framework model that was based on the capsule networks to identify coronavirus-19 disease [16]. The recommended method uses a number of convolutional layers as well as capsules to handle complications of class imbalance. The investigations confirmed that the COVID-satisfactory CAPS performed well on less-trainable parameters. It was cited as the carefully trained model, openly accessible on Github [17]. They arrived at the conclusion that, despite utilizing fewer trainable parameters, the suggested model demonstrates accuracy, sensitivity, and specificity values of 95.7%, 90%, and 95.80%, respectively. The first three French instances of COVID-19 infection were examined; two were diagnosed in Paris while one in Bordeaux. Formerly developing the coronavirus-19 infection; residents in Wuhan, China [18]. An artificial intelligence-based hybrid system was developed by the scientists that specifically combined deep learning as well as machine learning (using a Softmax classifier) [19].

The recommended method was intended exclusively for the identification of COVID-19 patients from the CT scan images. A study conducted a radiologic investigation of the novel coronavirus that caused Middle East Respiratory Syndrome. A 30-year-old guy was observed who had diarrhea as well as a fever and stomach pain. The patient was diagnosed and treated using chest CT scan [20]. The significant outcomes were obtained by using a dataset of chest CT scans. A discussion of the precautions that hospital staff must take when caring for patients who are infected with the COVID-19 virus was also presented. The hospital staff must follow specific protocols to decrease the risk to healthy patients. There was an investigation into what caused the pandemic in Wuhan, China. They also questioned the specific cause of this outbreak [21].

The author determined pneumothorax using the SVM method. They extracted the features of lung pictures using a local binary pattern (LBP). When contaminants from the CT scan images were eliminated, the suggested detection model used multi-scale texture segmentation to separate the regions of the aberrant lungs. In order to find numerous overlapping blocks, a texture change was also applied to this transformation. To find a whole region of disease with an aberrant component, the authors lastly employed a ride boundary (with Sobel Edge detection) [22]. The chest CT scans of twenty-one COVID-19 patients from Wuhan, China, were analyzed by certain researchers. The main attention of the authors is on how the coronavirus-19 disease affects the lungs of people [23].

The scientists then advised using a COVID-RENet model with CNN for classification to examine topographies (i.e., edge- and region-based). Before utilizing SVM to increase classification accuracy in this work, the authors used CNN to collect features [24]. This recommended approach is generally suitable for a medicinal practitioner for the initial diagnosis of people infected with the COVID-19 infection. A few researchers collected image files from CT scans of the chest for analysis of the effects in COVID-19 patients with pneumonia as well as lungs illness-infected patients [25]. Another investigation focused on the COVID-19 effect on the kidney as well as acute renal failure [26].

A 50-patient dataset with the COVID-19 was split into good and poor recovery groups. The flaking of viruses and antibodies was investigated. The scientists identify the risk factors for a prolonged recovery and lung infections. 58% of the patients had modest recoveries, according to the researchers' findings [27]. A study on the global total of the COVID-19-infected patients and fatalities is presented by certain authors [28]. Another way for the COVID-19 diagnosis was by using CT scan pictures. This was a deep learning-based method (Vector Gadget Classifier) [29]. By using this method, the COVID-19 infections can be rapidly identified in many patients. The 97.48% accuracy was revealed in the planned model for categorization of lungs by using a number of matrix parameters [30].

This paper's main goal was to present COVIDX-Net, a cutting-edge deep learning architecture that would aid medical professionals in independently diagnosing the COVID-19 disease by using the medical images. Also, talked about challenges and several methods for identifying the COVID-19 infection [31]. A computerized technique for the identification of COVID-19 infection should be designed to inhibit disease from spreading through touch. After reviewing a number of CT scan for pneumonia identification, it was concluded that it's not easy to determine whether the coronavirus was causing pneumonia or some other factors were present behind it. Lung problems were also being detected using chest radiography (CXR). The researchers show how CXR will be used by the medical community due to its total availability as well as decreased infection control [32]. Moreover, 123 frontal CT scan images were collected for the purpose of identifying COVID-19 infections [17, 33].

The researchers also discussed how AI tools are used in the medical field. A pre-trained as well as an updated CNN model from AlexNet was used on the acquired dataset. The 98.90% accuracy was shown by a pre-trained model, while CNN showed the model's accuracy at 94.1%. In order to create the sub-datasets, one hundred fifty CT scans and three thousand CT scan images that were marked with COVID-19 were divided into two subgroups (16*16 and 32*32, respectively) [34]. Fusion as well as ranking techniques was also used to improve a given method's performance. The scientists utilized a CNN model to transfer learning after categorizing the pre-processed data with SVM. The set 2 have good accuracy than set 1. A model was developed to recognize the coronavirus infection automatically from CT scan pictures of chest [35, 36]. Consideration was given to individuals who had confirmed coronavirus pneumonia and admitted to a hospital in Wuhan, China [11, 37].

To discover COVID-19 ailments, they made different groups of CT scan patients and then undertook further study, comparing features as well as the distribution of CT scan images. A KE Sieve Neural Network design to facilitate coronavirus-19 analysis by using CT scan images was also recommended by certain studies. The accuracy of their suggested model is 98.90% [37, 38]. Pneumonia analysis also made use of the CT scan dataset and a CNN-based approach. On CNN, two different models were used to transfer learning (the VGG16 and the InceptionV3). They kept employing SVM to discover superior results. The COVID-19 patients were accurately screened using a deep anomaly detection system. Following 100 CT scan image, 70 individuals had their COVID-19 status verified. They then discussed how COVID-19 impacts people [39]. A dataset containing one hundred and one cases of pneumonia with coronavirus infection was collected. Correlating CT imaging of COVID-19 pneumonia with its clinical status was the major goal of this investigation. A study of all the beliefs and theories put forth by numerous researchers indicates that coronavirus-19 is a viral infection that affects not only individuals but also a nation. They discussed several ways to easily locate COVID-19 occurrences.

3. Materials and Methods

The dataset used and the methodology used are explained in the subsequent sections.

3.1 Dataset

The dataset used was obtained from the Kaggle COVID-19 radiography database [40]. This dataset was constructed by collecting data from 7 public datasets to create a large CT scan dataset of the lungs for COVID-19 [41]. In this dataset, the CT images were divided into three classes, namely COVID-19, CommunityAcquired Pneumonia (CAP), and Normal. The COVID-19 CT images dataset was consist of

7593 COVID-19 CT images from 1196 patients, 2618 Pneumonia CT images from60 patients, and 6893 Normal CT images from 604 patients [40]. These datasets had been publicly used in the COVID-19 diagnostic literature and have demonstrated their efficiency in deep learning applications. The details of COVID-19 CT images dataset are given in Table 1.

Table 1. Dataset distribution

Type	Total Patients	Total Images
Normal	604	6893
COVID-19	1196	7593
Pneumonia	60	2618
Total	2990	17104

3.2 Data Preprocessing

Following data collection, the images were preprocessed using several preprocessingtechniques. These techniques could help with noise reduction and emphasizing sections of the image which was benefit during the model training. Image preprocessingis an important task for getting a sufficient result [42].

3.3 Data Splitting

The most common techniques for splitting the data are percentage split and k-fold cross-validation. Percentage split is a simple way to split data into training, validationand test sets. In this work, percentage split technique was used with 70:10:20 split ratio. From the total, 70% used for training, 10% used for validation, and 20% used for testing. Training set used for training the model, validation set used to evaluate the model during the training process, testing set used to provide an evaluation of the trained model. The same ratio of data splitting was used for both imbalanced and balanced datasets. The details of data splitting for initial and enhanced datasetsare given in Table 2 and Table 3.

Table 2. Details of training, validation and testing set for initial dataset.

Type	Training Set	Validation Set	Testing Set	Total
Normal	4825	689	1379	6893
COVID-19	5315	759	1519	7593
Pneumonia	1833	262	523	2618

Table 3. Details of training, validation and testing set for enhanced dataset.

Type	Training Set	Validation Set	Testing Set	Total
Normal	1750	250	500	2500
COVID-19	1750	250	500	2500
Pneumonia	1750	250	500	2500

3.4 Model Design

The data was collected from Kaggle as it was acquired and sanitized as necessary [43]. A large dataset was required to produce reliable results using the deep learning technique [12, 44]. Yet, it is probable that any topic lacks appropriate data, especially medical-related issues. Medical data collection can sometimes be expensive and time-consuming. With augmentation, it is possible to resolve these types of issues. In addition to preventing over fitting, augmentation also increases the accuracy of the proposed model. This collected dataset also utilizes augmentation to prevent over fitting. Among the enhancements were image sharing, rotation, and zoom. The information was then shifted to increase the applicability of the model and reduce over fitting. The suggested model was then trained using the collected dataset. Three different models were used to expand the analysis, while the correctness of each was determined by comparing their performances. Leaky ReLU activation was substituted for the original ReLU activation function in the presented models, constituting a new strategy. This technique accelerates training while reducing the problem of neuronal of neuron [43]. Figure 1 represents the abstracted form for the analysis of chest CT scan.

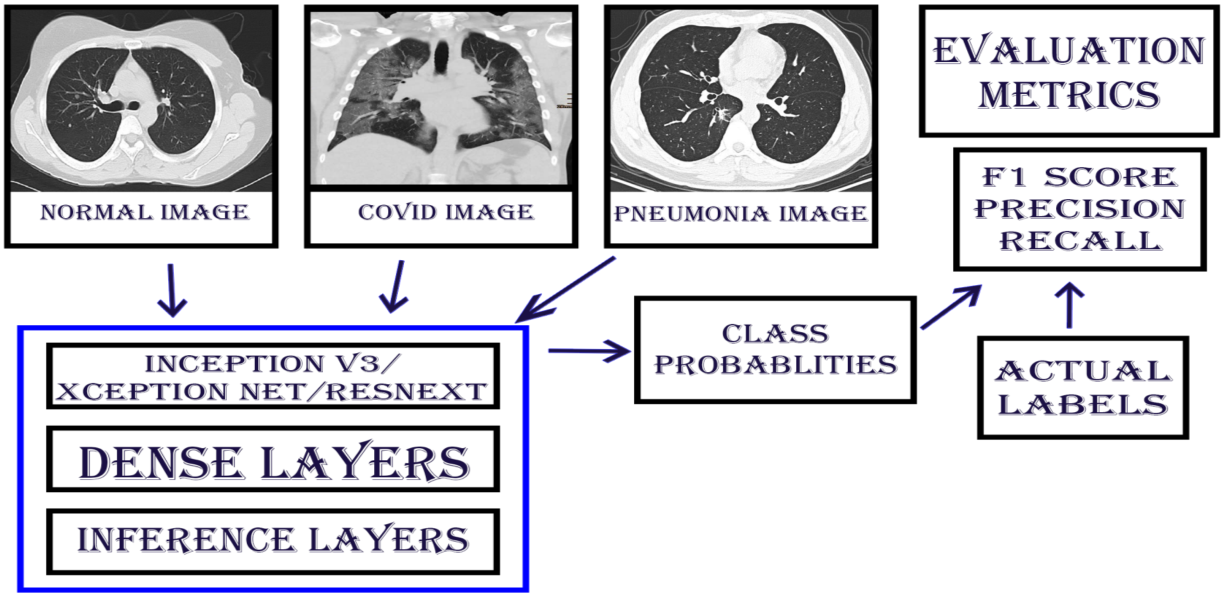

Figure 1. Proposed model for chest CT scan dataset evaluation

3.4.1 Inception net v3 model

The CNN-based classification network is known as Inception Net V3. It employs inception modules with 48 layers and a concatenated layer including 11, 33, and 55 convolutions. This allows us to accelerate training while minimizing the number of parameters. It is also known as the GooLeNet architecture [43]. Figure 2 represents the abstracted model for Inception Net.

3.4.2 Xception net model

This model is a modified version of the inception net model in which depth-wise separable convolutions replace the inception modules. It executes better than Inception Net despite having the same parameters as the latter. Figure 2 depicts the architecture of the Xception net model.

3.4.3 Resnext model

In the ResNeXt model, the typical remaining blocks have been exchanged for ones that utilize the split-transform-merge approach observed in the Inception model. Figure 2 depicts the architecture of the ResNext model [43].

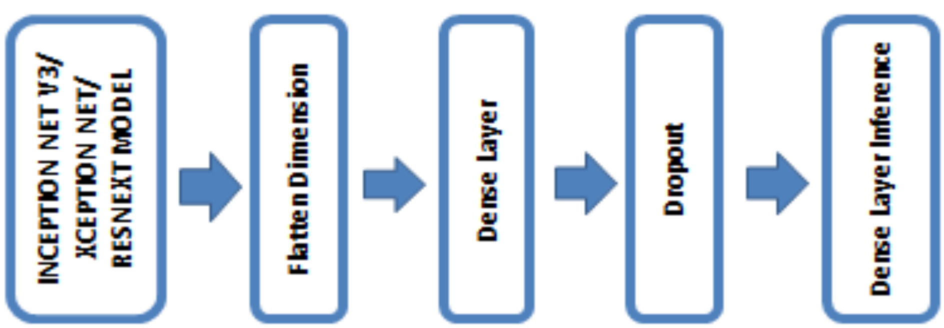

Figure 2. Abstracted form of models.

3.5 Loss Function Used : Categorical Cross-Entropy

It was applied to train our model and utilized to improve the model's parameter values. In each successive epoch, we wish to diminish the loss function. When learning rate = 0.001 is used to train the model, the Adam optimizer is employed to increase the parameter values.

$$L(Y, ¥) = -(\sum Y * \log(¥) + (1 - Y) * loglog(1 - ¥)) \quad (1)$$

In equation 1 the Y is the true label ; ¥ is the predicted label and L (Y, ¥) is the loss function [43].

3.6 Proposed Algorithm

The application strategy for the suggested models is described as follows:

Keras Data Generator was used for preprocessing of image X: Transform X to the coordinates (128; 12; 3); Random Rotation Range = 10 °; Horizontal Flip = True; Zoom Range = 0.4. Shape = (128; 128; 3) was recommended for rapid processing while Shape = (256; 256; 3) was for the improved performance. After that the image was applied for pre-training of the model's input and gets the output of the model's last convolution layer. Then Reduce n-dimensionality to level dimensions. A thick coating was applied that was 256 units for the XCeption Net as well as the Inception Net; 128 units for the ResNeXt.

$$Z = W * A + b \quad (2)$$

W = weight & b=bias

The activation was applying as

$$A = LeakyReLU(Z) \quad (3)$$

The dense layer was applying for the inference

$$Z = W \times A + b \quad (4)$$

The softmax was applying for the classification

$$softmax(Z_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{zj}} \quad (5)$$

$$\#LeakyReLU(Z) = max(0.01, Z)$$

3.7 Matrices Used for Evaluating Results

Sensitivity, specificity as well as precision, recall, and the F1 score, were utilized to evaluate the suggested models [43].

$$Precision = \frac{T\ P}{T\ P + F\ P} \quad (6)$$

$$Recall\ (Sensitivity) = \frac{T\ P}{T\ P + F\ P} \quad (7)$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

$$Specificity = \frac{T\ N}{T\ N + F\ P} \quad (9)$$

4. Results and Discussion

One of the common imaging modalities utilized in COVID-19 study is CT scan image. CT scans produce excellent 3D pictures that can be used for COVID-19 identification. There are numerous studies that use chest CT scan to diagnose COVID-19 using binary or multiple classifications. While some works use feature extraction, others use raw data. Moreover, there are variations in the quantity of photos utilized in the research. The convolutional neural network is the studies' recommended method (CNN) [45]. By adding more COVID-19 Chest CT scan pictures to the dataset, future studies can assess how well different CNN algorithms do in classifying images. The typical chest CT scan images and COVID-19-affected individuals were compared in this study [46]. Accuracy metrics were used to evaluate the Inception Net V3 model, the Xception Net model, and the ResNeXt model. In order to determine the optimal model, the outcomes were compared. Even though model accuracy is quite strong, we recommend using the next dataset updates to validate performance. A total of 1945 samples were used to train the model due to a shortage of data.

4.1 Xception Net Model

In this method, a modified form of inception net is used in which depth-wise separable convolutions are substituted for inception modules. The size of its parameter is comparable to that of the Inception neural network, but its performance is marginally superior. Table 4 and table 5 display f1-score of the training as well as the testing sets in the case of the XCeption net model [47].

Table 4. Training dataset.

Labels	Precisions (%)	Recalls (%)	f1-scores
COVID-19	99.13	100	98.45
Pneumonia	100	98.64	100
Normal	100	99.08	99.07

Table 5. Testing dataset.

Labels	Precisions (%)	Recalls (%)	f1-scores
COVID-19	95.32	94.86	98.05
Pneumonia	98.25	89.11	98.77
Normal	97.19	91.55	95.18

Figures 5 and 6 depict the outcome analysis of the training as well as the testing utilizing loss as well as accuracy in the case of the Xception net model.

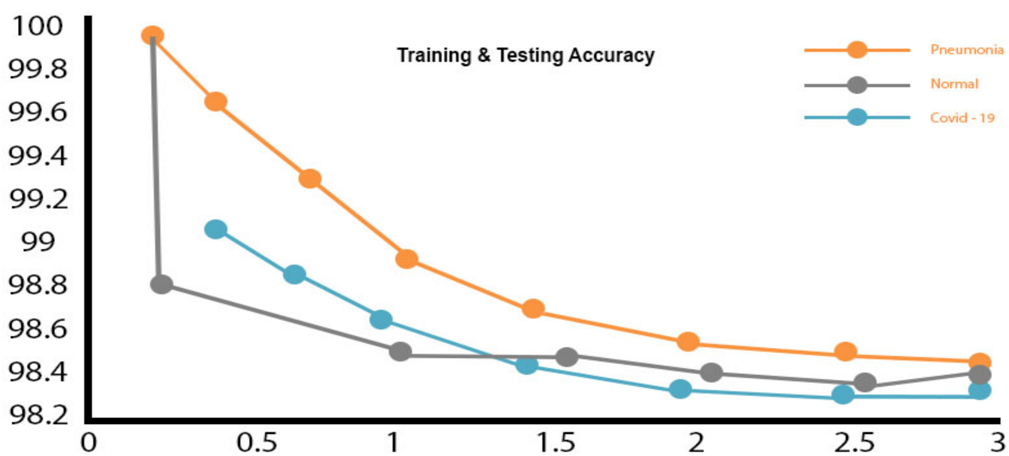

Figure 3. Training & testing accuracy of Xception net model.

Figure 4. Training & testing loss of Xception net model

4.2 Inception Net V3 Model

The CNN system for categorization was cutting-edge. It comprises forty-eight layers and employs inception modules, including a layer that is concatenated by 1 1, 3 3, and 5 5 convulsions. It speeds up training while minimizing the number of parameters. It also known as Google Net architecture. The tables 6 and 7 showed the f1-score of training as well as testing sets for the Inception V3 model.

Table 6. Training dataset.

Labels	Precisions (%)	Recalls (%)	f1-Scores
COVID-19	96.23	96.47	96.81
Pneumonia	98.75	95.01	98.54
Normal	99.12	99.03	99.17

Table 7. Testing dataset.

Labels	Precisions (%)	Recalls (%)	f1-Scores
COVID-19	95.72	95.42	98.36
Pneumonia	97.19	93.33	94.24
Normal	96.52	97.38	94.05

Figures 7 and 8 demonstrate the Inception Net model training loss, which lowers over subsequent epochs.

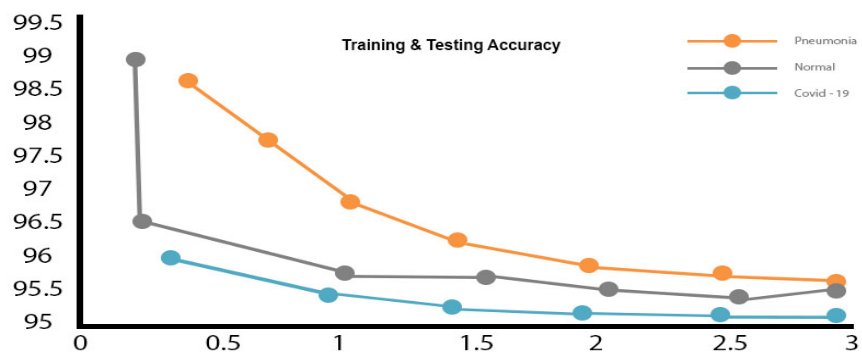

Figure 5. Training & testing accuracy of Inception net V3 model.

Figure 6. Training & testing loss of Inception net V3 model.

4.3 Resnext Model

This architecture expands upon the deep residual network. The tables 8 and 9 show the f1-scores of training as well as the testing set of the ResNeXT model, respectively.

Table 8. Training dataset.

Labels	Precisions (%)	Recalls (%)	f1-Scores
COVID-19	89.18	94.34	91.36
Pneumonia	92.56	96.28	90.08
Normal	91.23	90.62	94.78

Table 9. Training dataset.

Labels	Precisions (%)	Recalls (%)	f1-scores
COVID-19	97.47	99.13	95.11
Pneumonia	99.16	98.76	97.65
Normal	99.25	96.82	99.19

Figure 7 illustrates the accuracy of the ResNeXt model as it progresses through various epochs, whereas Figure 10 does the same for the ResNeXt model as it advances through various epochs. Even though our ResNeXt model is sensitive to over fitting, it is still the most accurate. Results showed that XCeption Net performed better than all other models.

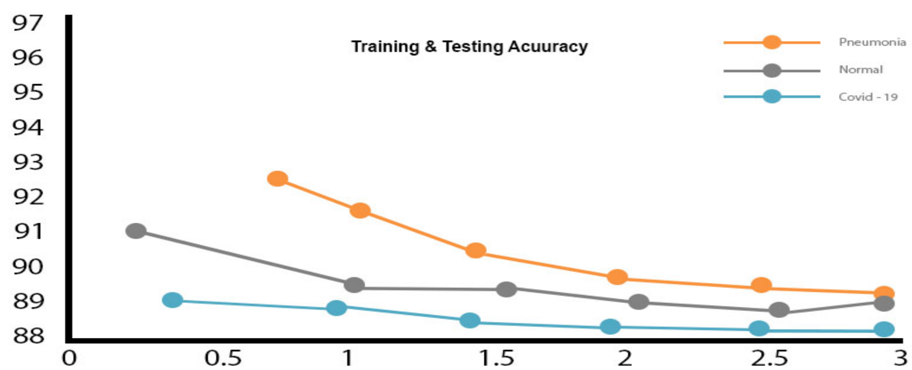

Figure 7. Training & testing accuracy of ResNeXt model.

Figure 8. Training & testing loss of ResNeXt model.

5. Conclusion

For any practical use of these findings, medical specialists should also be consulted. We would rather examine possible, financially viable techniques for combating this disease than develop a perfect detection system. Similar strategies could be followed for additional research to indicate that the COVID-19 outbreak is escalating daily. When the number of cases increases, it may be essential to test multiple cases simultaneously. In this study, we evaluated several CNN models to classify patients with coronavirus infection on the basis of their chest CT scan. It has been evaluated that the XCeption net performs best, which is the most applicable.

6. Future Work

We have successfully categorized COVID-19 pictures, demonstrating the potential application of such algorithms in the future for diagnostic purposes. The high level of achieved precision might be concerning because it could be the outcome of over fitting. It can be confirmed by comparing newly collected data, which will soon be made public. The massive chest CT scan dataset could one day be utilized to validate our actual implementation.

Acknowledgement: The authors are thankful to all the people who provide support to complete this work.
Conflicts of Interest: No conflict of interest.

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