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COVID-19IraqKirkukDataset: Development and evaluation of an Iraqi dataset for COVID-19 classification based on deep learning

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Abstract

In the last two years, the coronavirus (COVID-19) pandemic put healthcare systems around the world under tremendous pressure. There have been intelligent systems (Machine Learning (ML) and Deep Learning (DL)) able to identify COVID-19 from similar normal diseases. The algorithms use Imaging techniques (like Chest X-Rays) in classifying COVID-19. Therefore, many global COVID-19 datasets have been released. However, so far, no public local Iraqi dataset has been developed. Therefore, our contribution is two folds. First, we investigate the techniques of deep learning techniques in COVID-19 classification. Second, we develop a new COVID-19 dataset, namely, "Covid-19IraqKirkukDataset" collected from hospitals in Kirkuk, Iraq. To the best of our knowledge, our dataset is the first COVID-19 dataset. Then, the evaluation of Covid19IraqKirkukDataset using Convolutional Neural Networks (CNNs) demonstrates promising classification outcomes.

Keywords: COVID-19, Deep learning, Convolutional Neural Networks, dataset, X-rays
2020 MSC: 68T07, 68T09

1 Introduction

In March 2020, the World Health Organization (WHO) declared coronavirus disorder (COVID-19) a global pandemic. COVID-19 is an infectious disease reverted by the SARS virus. The massive COVID-19 outbreak infected 223 countries, resulting in over 637 million cases of infection and 6.6 million fatalities worldwide [19]. Cases of infection and mortality are growing fast. Figure 1 shows the COVID-19 death rate in 16 months (from 22 January 2020 to 06 April 2021) [17]. COVID-19 diagnosis is fairly difficult, given the economic concerns posed by the high cost of diagnostic testing in developed and developing nations. Insufficiency of clinical diagnosis procedures is one of the most important causes of the rapid spread of COVID-19 [18].

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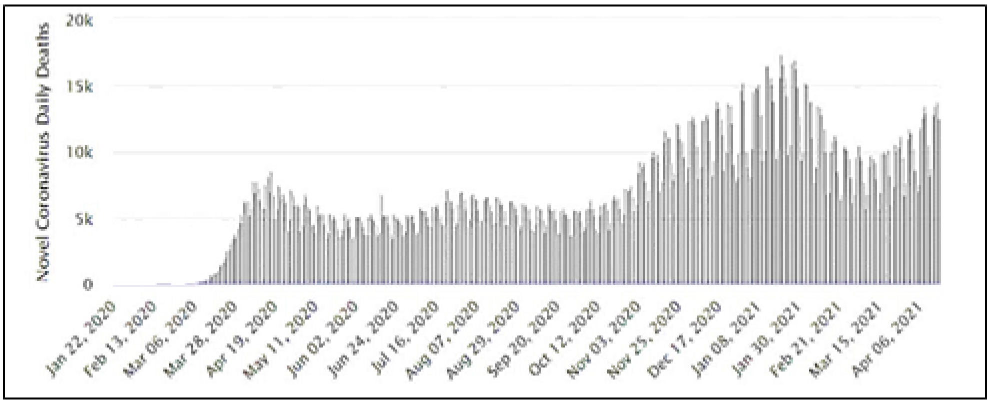

Figure 1: Global COVID-19 death rates in 16 months [17]

Chest X-Ray (CXR) is generally available in the majority of clinical settings and requires less time for patient preparation and fast diagnosis. CXR can therefore be used for patient triage, determining the priority of patient therapies, and allocating medical resources [5]. Deep learning (DL) approaches have been utilized to dramatically increase the performance of image analysis in the medical imaging area. DL has been effectively applied to microscope images, MRI images, brain cancer classification, and retinal shots. Deep learning artificial neural networks, such as Convolutional Neural Networks (CNNs), have proven to be highly effective in many medical image classification applications [4].

CNNs are typically utilized for medical imaging. There are several structures and applications. Using CXR images, many studies proposed and implemented DL techniques to identify COVID-19 accurately. Using CXR images, comparison of DL techniques and understanding their works may help to classify COVID-19 [14].

This article is organized as follows: Section 2 provides a critical literature review on implementing Deep learning techniques in COVID-19 identification published in highly ranked journals, such as IEEE, Scopus, and Springer. Section 3 explains the Convolutional neural networks in detail and defines datasets and their use in training, testing, and validation procedures with Software and hardware requirement. Evaluation metrics are described in Section 4 . Section 5 evaluates model performance on local and global datasets. Finally, we conclude the paper in Section 8. Figure 2 highlights the road map of this paper.

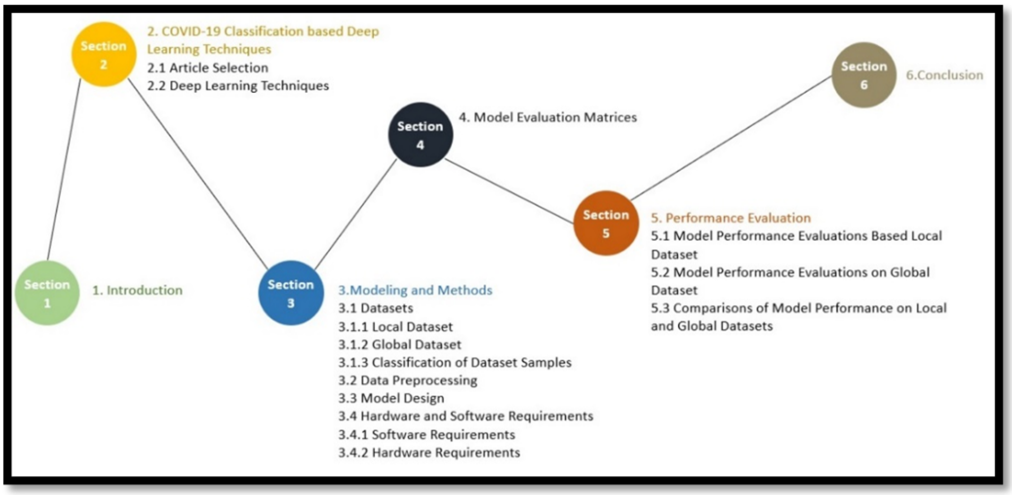

Figure 2: Organization of the paper

2 COVID-19 Classification based Deep Learning Techniques

2.1 Article Selection

This study enhances our knowledge of the literature by evaluating and analyzing prior studies on the topic. Recent research has focused on developing effective techniques that employ DL systems that classify COVID-19. To simplify the analysis, 16 recent papers were analyzed to understand the existing studies.

The search was carried out as follows: “Coronavirus” AND “Deep learning” (“Covid” OR “COVID-19” OR “Classification” OR “Classifier” OR “Deep learning” OR “Convolutional Neural Networks” OR “CNNs” OR “ResNet-50” OR “ResNet101” OR “ReNet1” OR “ReNet2” OR “DenseNet” OR “MobileNet” OR “VGG16” OR “VGG19” OR “SqueezeNet” OR “InceptionV3” OR “Xception”).

2.2 Deep Learning Techniques

According to the literature, deep learning techniques used in COVID-19 classification have been categorized into four techniques:

1. Novel deep learning architecture.
2. Direct use of deep learning.
3. Transfer learning fine-tuning technique.
4. Transfer learning feature extraction technique.

The author in [7] designed and proposed a novel and robust CNN model for detecting COVID-19 disease using publicly available datasets. This model was verified to determine whether the patient is infected with COVID-19 and achieved an accuracy of 99.20%. In another study, in [6], the CoroDet model was developed to achieve accurate diagnostics in three cases: 1) four classes classification (COVID-19, Normal, non-COVID-19 viral pneumonia, and non-COVID Bacterial Pneumonia), 2) three classes classification (COVID-19, Normal, and non-COVID-19 Pneumonia), and 3) two classes classification (COVID-19 and Normal). CoroDet revealed a high accuracy performance of 91.2%, 94.2%, and 99.1% in the 4, 3, and 2 classes classification cases, respectively.

Similarly, the DarkCovidNet model was proposed in [16]. In the study, the authors proposed a 17-layer CNN model to achieve accurate diagnostics in two cases: 1) three classes classification and 2) two classes classification. The accuracy of the cases was 87.02% in the three classes classification, whereas it was 98.08% in the two classes classification. In work in [12], two novel custom CNN architectures, namely COVID-RENet-1 and COVID-RENet-2, were developed. The proposed technique systematically employs Region and Edge-based operations along with convolution operations. The performance was a good result, with an accuracy of 98%.

Three phases model was applied in [11]. Initially, datasets were acquired from four different sources. After that, the authors used image augmentation techniques to improve the training process efficiency. Lastly, the authors applied the pre-trained ResNet50 model of CNN to extract deep features on CXR images (to distinguish between COVID-19 and nonCOVID-19 patients). The results proved the model’s performance with an accuracy of 99.5%. The authors in [3] trained 201 layers DenseNet after downloading the pre-trained model on ImageNet. Then they trained the model on the COVID-19 dataset. After using the transfer learning approach, the accuracy was raised to about 99.3%. As pre-trained on Image Dataset, the authors [8] utilized the architectures of the four models ResNet50, Xception, Inception V3, and MobileNet. The four models’ accuracy indicated that CNN architectures are more dependable for Covid-19 patients. The results MobileNet achieved the maximum performance in terms of F score, with the highest accuracy of 98.6%. The accuracy of the rest models reached: 98.1%, 97.4%, and 82.5% in Inception V3, Xception, and ResNet50, respectively. Three different CNN models, InceptionV3, Inception- ResNetV2, and ResNet-50, were evaluated in [15] to classify COVID-19 from the CXR images. ResNet50 provided better classification accuracy of 98% than the other models.

The procedure transfer learning was adopted in the model proposed in [2] for two types (two and three classes). The model behaved better in two classes type (98,75%), while it was 93.48% in three classes. The authors in [26] evaluated the effectiveness of AI in the rapid and precise identification of COVID-19 from chest X-Ray images. Fine-tuned and -trained deep learning algorithms were used to improve the accuracy of the algorithms. The test demonstrated that MobileNet and VGG16 achieved the best accuracy of 98.28%.

Extensive tests were conducted in [28] to prove the superiority of AI-based structures over several models. With a Bayesian optimization additive, SqueezeNet was utilized to diagnose COVID-19. The critical success led to outperforming the suggested model, fine-tuned hyperparameters, and augmented datasets. The study determined a higher

COVID-19 diagnosis accuracy of 98.26%. In [29], the authors developed a model using a transfer learning approach and pre-trained customized models. ResNet50, MobileNetV2, InceptionV3, and VGG16 extracted deep features. The model showed the train and test accuracies as 93% and 98%, respectively.

ShuffleNet for the automatic extraction of features was used in [1]. Then, four classifiers were fed by the features: KNN, SVM, Softmax, and Random Forest. Via ShuffleNet features, different accuracies were achieved. Bot Random Forest and SVM obtained the highest at 99.35%, whereas Softmax was 95.81%, and KNN was 80%.

In [10], transfer learning from the Residual Network (RESNET-50) was utilized for model creation on chest x-rat pictures from healthy persons, bacterial and viral pneumonia, and COVID-19-positive patients. For COVID-19 inference, the performance metrics were revealed as follows: accuracy (99%), recall (99.8%), precision (99%), and F1 score (99.8%). The authors in [20] used pre-trained knowledge using transfer learning techniques and compared different CNN architectures' performances. The proposed model, DenseNet201, provided an excellent classification accuracy of about 98.75%. In [23], the SVM was evaluated for detecting COVID-19 using the deep features of 13 CNN models. The model produced the best outcomes using the deep feature of ResNet50. Both SVM ResNet50 achieved the highest accuracy, 98.66%. Finally, Figure 2 compares the studies in terms of detection accuracy.

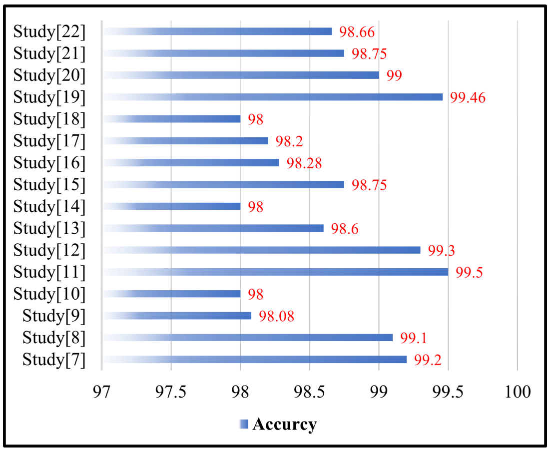

Figure 3: The achieved accuracy of all studies reviewed in related work

3 Modeling and Methods

To achieve our goal, the work is divided into three phases. Firstly, collect the datasets from local and global sources. Secondly, use image augmentation techniques to improve the training process efficiency and avoid an imbalanced dataset problem. Lastly, apply the pre-trained Resnet 50 model of CNN and use transfer learning direct use of the pre-trained model technique to extract deep features on CXR images collected locally and globally. Figures 3 and 4 show the adopted methodology of our work.

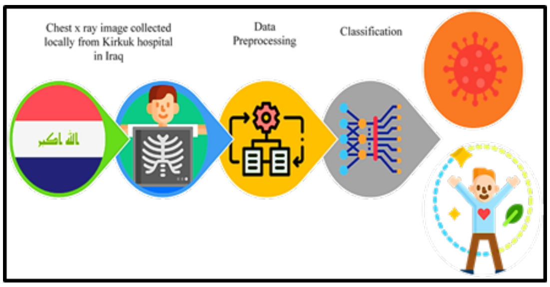

Figure 4: Methodology progress of data collected locally

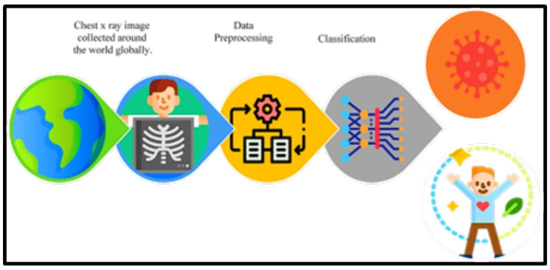

Figure 5: Methodology progress of data collected globally

3.1 Datasets

Dataset availability is crucial in training and testing the models. Furthermore, since COVID-19 is a new type of coronavirus, scholars face challenges finding the COVID-19 dataset in Iraq. Therefore, in this paper, we decided to evaluate our CNN model using the following datasets:

3.1.1 Local Dataset

Due to the absence of an official COVID-19 dataset in Kirkuk, Iraq, we realized the necessity to generate a local dataset by collecting data from different sources (hospitals) and making it available globally. The generated dataset may help scholars in Iraq and around the world to design and verify their studies.

We started looking for ways of getting data from Radiologists and private companies that provide Kirkuk hospitals with CXR equipment. Then, we discussed with a scientific and medical committee in Kirkuk Health Department about creating a public COVID-19 dataset of the Kirkuk patients. After that, we obtained the required approvals and started collecting CXR data for COVID-19 patients from hospitals in Kirkuk. As listed in Table 1, the hospitals are as follows:

1. Al-Shifa Hospital.
2. Kirkuk General Hospital.
3. Azadi Teaching Hospital.

We collected 340 CXR images categorized as 250 COVID-19 and 90 non-COVID-19. The infected samples were collected from Al-Shifa Hospital. On the other hand, we obtained non-COVID-19 data from Kirkuk General Hospital and Azadi Teaching Hospital.

Table 1: Locally collected data from hospitals in Kirkuk

Location	Class of cases	No. images
Al-Shifa Hospital	Covid-19	250
Kirkuk General Hospital	Normal	50
Azadi Teaching Hospital	Normal	40

Then, we named this dataset “Covid19IraqKirkukDataset” and released it to be available on Kaggle. Kaggle, a subsidiary of Google, is an online community of data scientists and ML practitioners. Furthermore, Kaggle allows users to find and publish datasets. Moreover, it helps explore and build models in a web-based data-science environment. Besides, it supports data scientists and ML engineers in tackling data science challenges [9]. Finally, “Covid19IraqKirkukDataset” is available and may contribute to ongoing research in Iraq and worldwide.

3.1.2 Global Dataset

Data in this part was collected from open sources and public repositories, which were collected from hospitals in different countries. From the Kaggle repository, we collected a similar number of samples, 250 healthy and 250 COVID-19 patients’ CXR images. It was gathered from the COVID-19 Radiography database, which is the winner of the COVID-19 Dataset Award. It is a dataset composed of six different sources, including the RSNA Pneumonia Detection Challenge dataset, the Twitter COVID-19 CXR Dataset, the COVID-19 Image Data Collection, and the SIRM COVID-19 Database [31]. Table 3 summarizes the globally collected data details.

Table 2: Globally collected data from the COVID-19 Radiography Database

Dataset	Class of cases	No. Images
COVID-19Radiography Database	**Covid-19**	**250**
COVID-19Radiography Database	**Normal**	**250**

3.1.3 Classification of Dataset Samples

As a part of this section, we divided the dataset into training and testing sets to examine our model. Note that this is the first model evaluated by a local dataset. As listed in Table 3, the samples in the local and global datasets are split into train and test data with a ratio of 70:30 percent, respectively. This means that the number of samples in both local and global datasets is 200 and 50 for training and testing, respectively.

Table 3: The ratio of train and test sets of local and global datasets

Dataset	Train		Test	
	Percentage	No	Percentage	No
Local Dataset	70	175	30	75
Global Dataset	70	175	30	75
Total		350		150

3.2 Data Preprocessing

To train any model, large amounts of data are necessary to achieve high prediction accuracy [25]. Therefore, the lack of data for COVID-19 patients is the main cause of designing unreliable models. Furthermore, the overfitting problem of the DL model stands out in small data sets (i.e., a low accuracy rate[13]).

The data augmentation technique is widely used to overcome this issue and improve accuracy. Simply, the data augmentation technique increases the number of samples from the existing sample. Its methods are: rotate, shear range, zoom range and flipping [24]. Because of the small number of normal case images in the local dataset, we used the data augmentation technique by flipping images vertically and horizontally to avoid overfitting. Consequently, after augmentation, we got equal data in both COVID-19 and normal cases (see Table 4).

Table 4: The total data collected locally and globally after applying the augmentation technique for triaging stage

Dataset	Classes of Cases	No. Images
Local	Covid-19	250
	Normal	250
Global	Covid-19	250
	Normal	250
Total	500	

3.3 Model Design

Instead of presenting our architecture, we drew knowledge from a pool of already existing CNN architectures that demonstrated great performance across a wide range of classification tasks. CNN model is used to determine whether or not a patient's CXR image contains COVID-19.

Residual Networks demonstrated faster training and a strong combination of performance and numerous factors. We employ the residual neural network with a total of 50 layers called Residual Networks with a depth of 50 (ResNet50). ResNet50 is a robust and powerful CNN architecture used for COVID-19 disease detection. It is important to mention that ResNet is among the top-five error rates under 3.6% [21]. Furthermore, The residual network architecture is capable of feeding images of sizes for which it has not trained. This is a critical part of the training methodology employed for training a high-performance network with very few epochs [30].

Figure 5 illustrates the design procedure of Resnet50 architecture, where the ResNet50 model has five stages, each with a convolution and Identity block. Each convolution block has three convolution layers, and each identity block has three convolution layers. More than 23 million trainable parameters exist in ResNet-50. The weights used in ResNet50 are pre-trained with the ImageNet dataset [27].

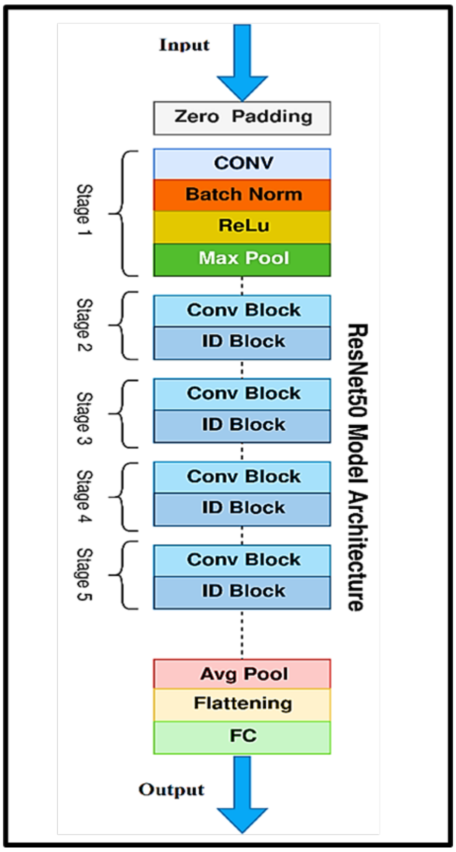

Figure 6: Architecture of Resnet 50 model

3.4 Hardware and Software Requirements

The hardware and software environments that are used in designing our model are as follows:

3.4.1 Software Requirements

- **Operating system:** Windows 11 Home, 64-bit operating system, x64-based processor.
- **Coding environment:** Visual studio code 2022.
- **Python framework:** 3.9
- **Artificial intelligent library:** Keras and TensorFlow.

3.4.2 Hardware Requirements

For training the model, we used a personal laptop that has the following specifications:

- **Processor:** Intel(R) Core (TM) i5-8265U CPU 1.60GHz, 1.80 GHz.
- **RAM:** 8 GB.
- **GPU:** internal display with Intel(R) UHD Graphics 620, 4 GB

4 Model Evaluation Matrices

Several metrics, such as precision, accuracy, sensitivity, and specificity, evaluate any ML and DL models in the literature. In this subsection, we introduce the reader to these evaluation parameters. Table 5 lists the four main parameters that use in calculating the performance of any model:

Table 5: Parameters of performance evaluation

Measurement	Acronym	Description
True Positive	TP	The sample is classified as true correctly
False Positive	FP	The sample is classified as true incorrectly
True Negative	TN	The sample is classified as false correctly
False Negative	FN	The sample is classified as false incorrectly

After obtaining TN, TP, FP, and FN, we can calculate performance metrics as follows.

Accuracy: It refers to the proportion of accurate anticipation to the total number of estimates. It is formulated as follows.

$$Accurcy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

Specificity: It is related to the classer's ability to detect negative consequences [22]. Specificity is expressed as follows.

$$Specifity = \frac{TN}{TN + FP} \tag{4.2}$$

Sensitivity: It can be obtained by proportioning the total number of correctly estimated data to the aggregate number of correct data. Sensitivity is written as follows.

$$Sensitivity = \frac{TP}{TP + FN} \tag{4.3}$$

Precision: The Precision value is obtained by dividing the aggregate number of classified positive samples by the estimated aggregate number of positive samples. It is obtained as follows.

$$Precision = \frac{TP}{TP + FP} \tag{4.4}$$

One of the most important criteria in CNN architectures to check its performance is the confusion matrix and accuracy/ loss figure [22]. Also, the model performance can be evaluated by a confusion matrix. It allows the visualization of the performance of a model.

5 Performance Evaluation

We used a personal laptop with Intel(R) Core (TM) i5-8265U CPU 1.60GHz, 1.80 GHz,8 GB of Ram and an internal display with Intel(R) UHD Graphics 620, 4 GB. The experiments were developed and trained using Visual studio editor, python programming language and Keras library. The model ratio of training and testing has been set to 70:30. In the following sections, we evaluate and discuss the results obtained by our model (pre-trained model Resnet50) on the local and global datasets.

5.1 Model Performance Evaluations Based Local Dataset

Figure 6 illustrates the performance of our Resnet50 Model based on our generated dataset. The figure demonstrated that the classification accuracy improves as the number of epochs increases. Specifically, training classification accuracy reached 99.43% with a 0.0461 training loss. Additionally, we obtained a validation accuracy of 84.67% with a 0.4581 Validation loss.

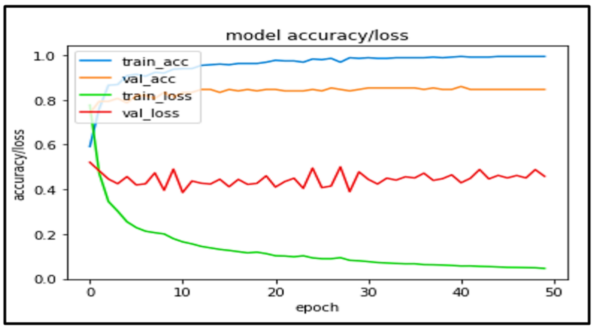

Figure 7: Curves of model training and validation Accuracy and loss on the local dataset

Accordingly, we draw the confusion matrix of our model classification Figure 7. One can see from the figure that only 20 out of 75 COVID-19 images are included in the normal (i.e., false negative) class. Besides, only 3 out of 75 normal (non-COVID-19) images were classified as COVID-19 (i.e., false positive).

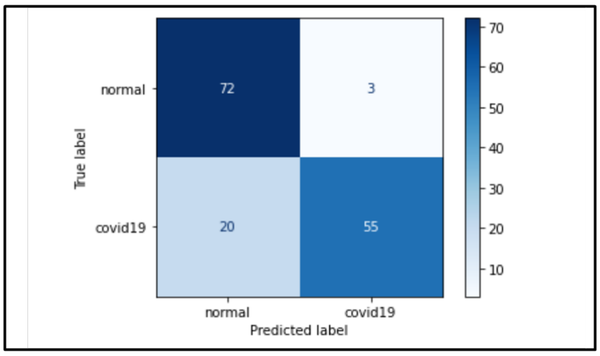

Figure 8: Confusion matrix of the model-based local dataset

5.2 Model Performance Evaluations on Global Dataset

Similarly, however, based on a global dataset, Figure 8 illustrates the performance of our Resnet50 Model based on our generated dataset. The figure demonstrated that the classification accuracy improves as the number of epochs increases. By contrast, the train and validation losses decrease as the number of epochs increases. Specifically, training classification accuracy reached 99.71% with a 0.0358 training loss. Additionally, we obtained a validation accuracy of 94.67% with a 0.1246 Validation loss.

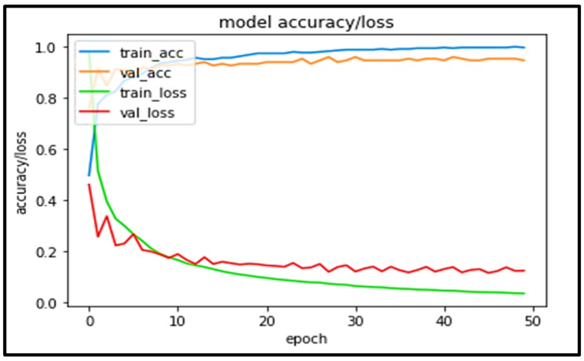

Figure 9: Curves of model training and validation Accuracy and loss on global data

Accordingly, we draw the confusion matrix of our model classification Figure 9. One can see from the figure that only 2 out of 75 COVID-19 images are included in the normal (i.e., false negative) class. Besides, only 6 out of 75 normal (non-COVID-19) images were classified as COVID-19 (i.e., false positive).

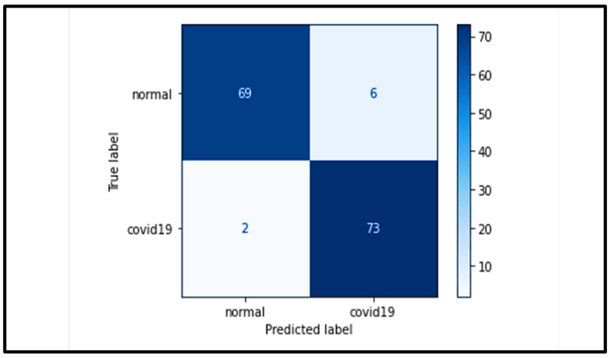

Figure 10: Confusion matrix of the model on the global dataset

5.3 Comparisons of Model Performance on Local and Global Datasets

Table 6 compares the outcomes of the model evaluation using local and global datasets. It is clear the training accuracy is almost equal in both datasets' training steps. However, the validation accuracy of each dataset is different, where the local dataset achieved 84.67 and the global dataset 94.67. The best explanation is that the number of images in the local dataset is less than in the global dataset.

Table 6: Comparison between model performance in a local and global dataset

Dataset	Classes	Data Portion			TP	FP	TN	FN	Training		Validation	
		Training set (70%)	Validation set (30%)	Total					Accuracy	Loss	Accuracy	Loss
Local	Normal	175	75	250	55	20	72	3	99.43	0.0461	84.67	0.4581
	Covid	175	75	250								
Global	Normal	175	75	250	73	2	69	6	99.71	0.0358	94.67	0.1246
	Covid	175	75	250								

6 Conclusion

After gathering global and local datasets in this paper, we split each dataset into training and validation sets. Then, we evaluated the model in both datasets in case of several criteria, such as the number of data, classes of data, a portion of data, confusion matrix details, accuracy, and loss.

Using the local dataset, the outcomes demonstrated that the training classification accuracy reached 99.43% with a 0.0461 training loss. Additionally, we obtained a validation accuracy of 84.67% with 0.4581 Validation loss. Similarly, using the global dataset, training classification accuracy reached 99.71% with a 0.0358 training loss. Additionally, we obtained a validation accuracy of 94.67% with a 0.1246 Validation loss. Therefore, the results demonstrated that the model training using the global dataset had more prediction accuracy than the local dataset. It is because the numbers and quality of data in the global dataset are better than in the local dataset.

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