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An Effective Deep Learning Model to Discriminate Coronavirus Disease From Typical Pneumonia

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ABSTRACT

Current technological advances are paving the way for technologies based on deep learning to be utilized in the majority of life fields. The effectiveness of these technologies has led them to be utilized in the medical field to classify and detect different diseases. Recently, the pandemic of coronavirus disease (COVID-19) has imposed considerable press on the health infrastructures all over the world. The reliable and early diagnosis of COVID-19-infected patients is crucial to limit and prevent its outbreak. COVID-19 diagnosis is feasible by utilizing reverse transcript-polymerase chain reaction testing; however, diagnosis utilizing chest x-ray radiography is deemed safe, reliable, and precise in various cases.

KEYWORDS

Chest X-Ray Images, COVID-19 Radiography Dataset, Developed Deep CNN Model, EfficientNetV2, InceptionV3

INTRODUCTION

In recent few years, human civilizations over the world have been threatened by emerging dangerous species of Coronaviridae termed Coronavirus disease (COVID-19) that has already given rise to millions of infected people and rapidly increased the death rate. Consequently, the early recognition infected cases is extremely significant to perform the

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medical treatment processes and the procedures of preventive containment (Abdel-Basset et al., 2021). Though numerous criteria provide successful COVID-19 diagnosis for people, the tools of clinical laboratory based on RT-PCR and sequencing of virus nucleic acid suffer from various deficiencies, such as the test results become prepared at the earliest twenty-four hours concerning crucial cases and usually require many days to dedicate a decision (Kumar et al., 2022). Recently, the world health organization announced that RT-PCR may provide incorrect results in COVID-19 cases owing to low-quality specimens obtained from patients, unsuitable specimens processing, and taking specimens at the late or early stages of the disease. The alternative common technique of COVID-19 diagnosing utilized today is Computed Tomography (CT). However, this technique is not easily accessible, and it is very costly. The majority common technique that medical specialists utilize for monitoring, triaging, and diagnosing varieties of pneumonia and COVID-19 disease courses is chest X-rays radiography. In contrast to RT-PCR and CT techniques, having a chest X-ray image is inexpensive and requires only a few seconds. Therefore, X-ray imaging holds a considerable possibility to be an alternate technique to other tools. The COVID-19 manual diagnosis may be prone to human error which leads to consuming time, and accordingly, this requires the help of adequate radiologists to realize high accuracy of diagnosis (Yamaç et al., 2021).

At present, various medical health issues and complications such as breast cancer diagnosis, brain tumor diagnosis, and many more are utilizing machine and deep learning models-based solutions (Fati et al., 2022; Mathiyazhagan et al., 2022; Mohanty et al., 2021; Flayyih et al., 2020; Hasan et al., 2020; Hussien et al., 2020; Inbarani et al., 2020; Kumar et al., 2019, 2015; Hassanien et al., 2014; Emary et al., 2014a,b; Aziz et al., 2013; Jothi et al., 2020, 2019a,b, 2013; Anter et al., 2013; Azar et al., 2013, 2012). The technology of deep learning can disclose the features of the image that are non-obvious in the original image (Boulmaiz et al., 2022, Zaidi et al. 2022; Azar et al., 2021; Koubaa et al., 2020; Elkholy et al., 2020; Ibrahim et al., 2020). Specifically, Convolutional Neural Networks (CNNs) have been mostly adopted via the community of researches (Al-Dulaimi et al., 2022; Ramadan et al., 2022; Aslam et al., 2021). The recent developments of CNN models have appeared with a successful invention in the field of natural images analysis, and in other computer vision areas. These models are capable of extracting and learning enhanced representations of visual features. Such developments supply additional proof that optimal performance can be obtained via deep architecture (Deepalakshmi et al., 2021; Waleed et al., 2021). The CNN-based image recognition models have been capable of distinguishing a considerable number of targets, and the obtained recognition accuracies exceed the standard individual's level (Jiang, 2022). Therefore, it can be concluded that, deep CNN can be exploited for realizing such developments also in the COVID-19 discrimination too.

The contribution of this work is as follows:

- Implementing the schemes of feature extraction and classification using the proposed deep CNN model in addition to other two pre-trained CNN models.
- Specifying an optimum model that can easily discriminate COVID-19 from other classes using chest X-ray image with high accuracy.
- Conducting extensive experiments using a benchmark chest X-ray radiography dataset to investigate the performance of CNN models in differentiating normal, viral-pneumonia, and COVID-19 classes.

The remaining part of the article has been arranged as follows; In section Two, the related works in the literature are concisely introduced. Section Three clarifies the entire architecture of the proposed deep CNN model. The COVID-19 Radiography dataset description, performance evaluation metrics, and the discussion of the outcomes are summarized in Section Four. Lastly, Section Five discusses the main conclusions and future works.

RELATED WORKS

Covid-19 pneumonia's appearance in the images of chest X-rays frequently has low contrast, with blurred boundaries, and overlapping organs, therefore, the discrimination between Covid-19 and typical pneumonia cannot be easy for radiologists. To beat this difficulty, various models of deep learning are developed. There are various models of deep learning utilized to detect Covid-19 pneumonia using various chest X-ray image datasets proposed in the literature. However, the utmost challenge is to find an efficient and convenient model of deep learning to detect and classify Covid-19 pneumonia that satisfies all the performance metrics.

Chowdhury et al. (2020) trained, validated, and tested various pre-trained CNN models, named MobileNet-version2, ResNet18, ResNet101, Inceptionv3, VGG19, SqueezeNet, CheXNet, and DenseNet201 to classify normal and pneumonia patients utilizing chest X-ray images. Moreover, the approach of transfer learning was used to train these models. In this study, a new database was produced by integrating different public databases and additionally by acquiring images from cutting-edge published related articles. The experiments were accomplished to classify two classes, including normal and COVID-19, and three classes, involving normal, COVID-19, and viral-pneumonia. For the problem of two classes classification, DenseNet201 and CheXNet based transfer learning model with image augmentation approach were achieved better performance than other models and the obtained accuracies were 99.70%, and 99.96%, respectively. While classifying three classes, the DenseNet201 based transfer learning model with image augmentation approach was achieved better performance than other models and the obtained accuracy was 97.94%.

Arifin et al. (2021) proposed an early detection method based on two versions of MobileNet's with Single Shot Detection (SSD). The dataset utilized in that method was the COVID-19 Radiography Database. The developed version 2 model (SSD MobileNetV2) showed that the detection of chest X-rays with normal, COVID-19, and viral-pneumonia conditions were better than the version 1 model (SSD MobileNetV1), with an average accuracy of 94%. Furthermore, the version 2 model also provided low computational requirements. However, these proposed models require further optimization of CNN architecture to increase the accuracy.

YadanarWin et al. (2021) utilized some deep learning-based models using chest X-rays either to classify a specific case and discriminate COVID-19 from viral and normal pneumonia or to identify the indicatory COVID-19 bio-markers region. Firstly, the lung regions were pre-processed and segmented utilizing the method of DeepLabV3+, and then they were cropped. These cropped regions were utilized as entries to various CNNs to predict COVID-19. The utilized dataset there was non-balanced, consequently, to handle this issue, the class has been balanced utilizing weighted loss, and more chest X-rays were added for the minority class utilizing the process of image augmentation. Furthermore, under-sampling of the majority classes, over-sampling of minority categories, and a hybrid-resampling process of over-sampling and under-sampling. The optimal implementing models from every process were merged to yield an ensemble classifier based on two strategies of voting. Lastly, the CNNs' saliency map was used to identify the indicatory COVID-19 bio-markers regions. The highest result of accuracy was achieved utilizing an ensemble classifier of MobileNetV2, XceptionNet, DensetNet201, NasNetMobile, and InceptionResNetV2 (utilizing voting strategies) with the process of augmentation 99.23%.

Khan et al. (2022) utilized various CNN models, named MobileNet-Version2, NasNetMobile, and EfficientNetB1, to classify the infection of COVID-19 from other infections. In this study, the used dataset comprised multiple datasets acquired from Kaggle with four classes: normal, COVID-19, viral-pneumonia, and lung opacity. The image augmentation approach was implemented on the training the images of chest X-rays to overcome the issues of a small dataset and to have a balanced dataset class. To improve the model performance, the classification head was adapted by utilizing a layer of normalization in conjunction with a dropout layer. The EfficientNetB1 model with adapted classification head exceeded the other pre-trained models with an accuracy of 96.13%.

However, this study was focused only on improving the computational time. Therefore, to improve the models' performance, some optimization techniques could be utilized for selecting optimal features for the classification.

Aslan et al., (2022) proposed a COVID-19 diagnosis system using the COVID-19 Radiography database. In this system, lung regions segmentation was firstly carried out on the images of chest X-rays based on Artificial Neural Networks (ANNs). The features were then extracted based on eight CNN models, named MobileNet-Version2, Inceptionresnet-Version2, Inception-Version2, AlexNet, GoogleNet, Densenet201, ResNet18, and ResNet50. After that, these features were classified into three classes, including normal, COVID-19, and viral-pneumonia using various machine learning techniques which are named as, Decision Tree, k-Nearest Neighbors, Naive Bayes, and Support Vector Machine. Furthermore, the hyper-parameters of these techniques were determined utilizing the Bayesian optimization to attain a successful classification accuracy. However, hyper-parameters optimization slowed down the speed of diagnosing. The experimental results in this work illustrated that the DenseNet201 model and Support Vector Machine outperformed the other models, and the accuracy was obtained as 96.29%. To enhance the performance of this proposed system, several modifications should have been provided. It could be preferable to utilize another optimization technique which should be appropriate in the calculation time. Also, it is significant to utilize a feature selection algorithm to determine the effective and robust features.

The majority of mentioned related works were dependent on constructing a particular neural network model having a particular number of layers or utilizing pre-trained neural networks. When the model layers were increased beside the complication of the features to be extracted through the network to accomplish the needed tasks, the computation complexity would be increased without any improvement in the model accuracy. Additionally, the usage of a few layers could minimize the model accuracy due to the fact that the features at the required complexity level were not detected. Thus, in order to accomplish reasonable performance in the terms of complexity and accuracy, a deep CNN model is proposed in this work to effectively categorize COVID-19, viral-pneumonia, and normal classes.

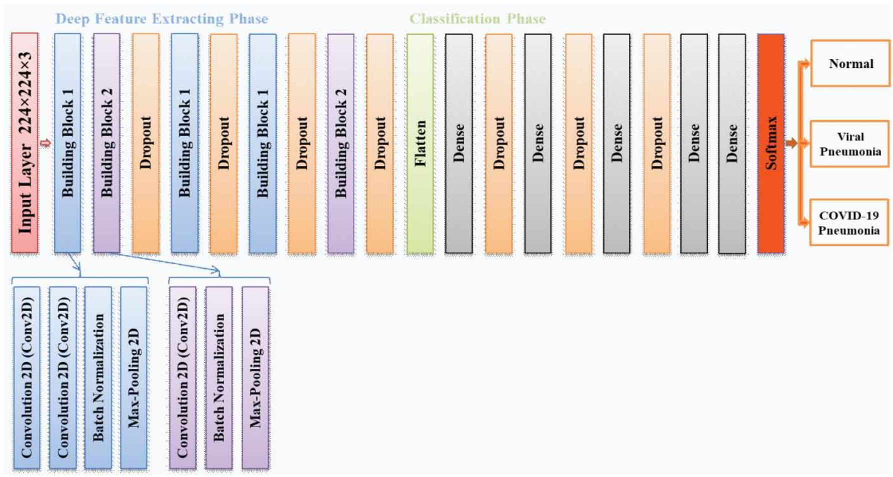
PROPOSED DEEP CNN MODEL

The models of deep learning have proven to be extremely accurate for guaranteeing superior prediction of various medical cases. Consequently, this section demonstrates the novel proposed deep CNN model, that accept a pre-processed (resized to 224×224×3 and normalized) chest X-ray image as input, and output a decision of classification among normal, viral-pneumonia, or COVID-19 pneumonia.

The novel proposed model is designed and trained several times using different parameters to choose the most preferable hyper-parameters and supporting a high-performing architecture. This proposed model includes two main phases. The deep feature extracting phase, in addition to the classification phase, as demonstrated in Figure 1.

The first phase includes five building blocks, each of which encompasses two convolutional layers with their ReLU activation functions followed by batch normalization (to minimize the training time and the network initialization sensitivity) and one Max pooling layer (of 2×2). But, the second and final building blocks include only one convolutional layer instead of two layers. The convolutional layers represent the basic units of the deep CNN model that are in charge of convolving the input image using learnable filters (of size 3×3) and extracting its deep features. The input image is slid through any filter for obtaining a feature map. The number of feature maps is specified by the number of filters. Max-pooling can be utilized in order to minimize the feature maps' dimensionality while preserving crucial information. The max-pooling layer works on minimizing redundant representations, yield from former layers, and consequently, controlling overfitting. No matter that the lack of learning

Figure 1. Proposed deep CNN model workflow



data can lead to the emergence of an overfitting problem (which means the obtained accuracy of training is much higher than the obtained accuracy of testing), which can also rise because of the massive amount of parameters within the neural network. To overcome this problem and to simplify the CNN model, the dropout algorithm is added at the end of each building block (except for the first block). The dropout algorithm works by temporarily removing some nodes from the neural network in accordance with the probability settings in the learning process. In other words, this algorithm removes the hidden fixed relationship between the nodes which may lead to improve the capability of anti-interference and to extent solving the mentioned overfitting problem.

In the second phase, after a flatten layer, there are five dense layers of different sizes with their ReLU activation functions, and among these only the first three dense layers are followed by dropout. Furthermore, the last dense layer with a Softmax activation function exists for three-class outputs.

In this novel proposed model, the number of non-trainable parameters is 1,984 and the number of trainable parameters is 15,249,731. The baseline of proposed model architecture is given in Table 1.

EXPERIMENTAL RESULTS

The experiments are conducted using an open-source dataset of chest X-ray images (explained in detail in the next sub-section). This dataset is split into 2 parts, consist of the training images (80%) to construct the model and consist of the testing images (20%) to tune and observe. it is then used to choose the most preferable model parameters. The three implemented models are fine-tuned for 100-epoch and the default batch size was 512. Regarding the proposed CNN model, 70 epochs arise out of the early stopping utilization to avoid model overfitting. The NADAM optimizer is applied to optimize the learning function with a learning rate of 0.0001. The whole chest X-ray images are resized to "224×224×3" and they are normalized before supplying them to the implemented models.

COVID-19 Radiography Dataset Description

COVID-19 Radiography dataset includes chest X-ray images with 299×299 pixels resolution for normal, viral-pneumonia, and COVID-19 conditions (COVID-19 Radiography Database-Kaggle, 2022). This dataset was created by a researcher team along with medical doctors,

Table 1. Proposed Model Architecture for Covid-19 discrimination

Layer_No. (Kind)	Output Shape	Parameters (P_s)
layer_1(Conv2D)	"_, 224, 224, 64"	1792
layer_2(Conv2D)	"_, 224, 224, 32"	18464
batch _normalization_0	"_, 224, 224, 32"	128
layer_3(Max-Pooling2D)	"_, 112, 112, 32"	-
layer_4(Conv2D)	"_, 112, 112, 64"	18496
batch _normalization_1	"_, 112, 112, 64"	256
layer_5(Max-Pooling2D)	"_, 56, 56, 64"	-
dropout(Dropout)	"_, 56, 56, 64"	-
layer_6(Conv2D)	"_, 56, 56, 128"	73856
layer_7(Conv2D)	"_, 56, 56, 128"	147584
batch _normalization_2	"_, 56, 56, 128"	512
layer_8(Max-Pooling2D)	"_, 28, 28, 128"	-
dropout_1 (Dropout)	"_, 28, 28, 128"	-
layer_9(Conv2D)	"_, 28, 28, 256"	295168
layer_10(Conv2D)	"_, 28, 28, 256"	590080
batch _normalization_3	"_, 28, 28, 256"	1024
layer_11(Max-Pooling2D)	"_, 14, 14, 256"	-
dropout_2 (Dropout)	"_, 14, 14, 256"	-
layer_12(Conv2D)	"_, 14, 14, 512"	1180160
batch _normalization_4	"_, 14, 14, 512"	2048
layer_13(Max-Pooling2D)	"_, 7, 7, 512"	-
dropout_3(Dropout)	"_, 7, 7, 512"	-
flatten(Flatten)	"_, 25088"	-
layer_14(Dense)	"_, 512"	12845568
dropout_4(Dropout)	"_, 512"	-
layer_15(Dense)	"_, 128"	65664
dropout_5(Dropout)	"_, 128"	-
layer_16 (Dense)	"_, 64"	8256
dropout_6(Dropout)	"_, 64"	-
layer_18(Dense)	"_, 32"	2080
layer_19(Dense)	"_, 16"	528
dense(Dense)	"_, 3"	51

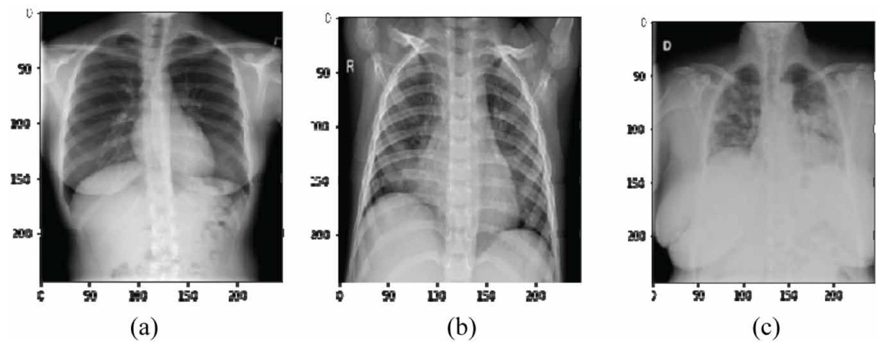
Trainable P_s: 15,249,731
Non-trainable P_s: 1,984
Total P_s: 15,251,715

and it is released in stages. In the final release, the dataset has included 10,192 normal, 1345 viral-pneumonia, and 3616 COVID-19 positive cases images, in addition to 6012 Lung Opacity images. However, totally only 15,153 chest X-ray images are acquired to be utilized in our work. The dataset description is given in Table 2, and some sample images from the dataset are demonstrated in Figure 2.

Table 2. COVID-19 Radiography dataset description

Classes	No. of images of chest X-rays
Normal	10,192
Viral-pneumonia	1345
COVID-19	3616
Total	15,153

Figure 2. Examples of (a) Normal, (b) Viral-pneumonia, and (c) COVID-19 positive cases images out of the COVID-19 Radiography dataset



As demonstrated in Figure 2, the main variation between the COVID-19 positive cases image and the typical pneumonia image is that pneumonia influences only a portion of the lungs, while COVID-19 influences the entire lungs.

Performance Evaluation Metrics

Several performance metrics are used to evaluate the performances of the proposed deep CNN model and the other two pre-trained models, in classification of the chest X-ray images. The first metric is the accuracy which can specify whether a model is trained properly or not. However, it cannot provide comprehensive information regarding its application to the issue. This metric is given in the following formula:

$$Accuracy_{Metric} = \frac{True_N + True_P}{True_N + True_P + False_N + False_P}$$

where *P* indicates "positive", and *N* indicates "negative". If the Covid-19 disease is the condition, then $True_P$ indicates the properly diagnosed Covid-19 diseased cases, and $False_P$ indicates the improperly diagnosed cases. While $True_N$ indicates properly diagnosed non-Covid-19 diseased cases, and $False_N$ indicates the improperly diagnosed non-Covid-19 diseased cases.

The second and third utilized metrics are recall (sensitivity) and precision which are considerably utilized in medicine. These metrics and their Macro-average are given in the following formulas:

$$Recall_{Metric} = \frac{True_P}{False_N + True_P}$$

$$Macro - Recall_{Metric} = \frac{\sum_{i=1}^{n} Recall_{Metrici}}{No.of\,Classes}$$

$$Precision_{Metric} = \frac{True_P}{False_P + True_P}$$

$$Macro - Precision_{Metric} = \frac{\sum_{i=1}^{n} Precision_{Metrici}}{No.of\,Classes}$$

The fourth metric is the F1-score which is employed to search for symmetry between recall and precision metrics. This metric and its Macro-average are given in the following formulas:

$$F1 - score_{Metric} = 2\frac{Recall_{Metric}\ .Precision_{Metric}}{Recall_{Metric} + Precision_{Metric}}$$

$$MacroF1 - score_{Metric} = \frac{\sum_{i=1}^{n} F1 - score_{Metrici}}{No.of\,Classes}$$

In order to clarify in-complete the weight-average formula, several steps should be followed; Firstly, specifying the weight of the whole data points; Secondly, multiplying the weight with each value; Thirdly, the outcomes of the second step are added together. Among the scores of weighted-average, weighted-average recall, weighted-average precision, and weighted-average F1-score are determined.

RESULTS AND DISCUSSION

To confirm the performance of the novel proposed deep CCN model, its evaluated results are compared with the results evaluated by use of two pre-trained learning models (InceptionV3 and EfficientNetV2 pre-trained models) which also accept a pre-processed (resized to 224×224×3 and normalized) chest X-ray image as input, and output a decision of classification among normal, viral-pneumonia, or COVID-19 pneumonia. These two pre-trained learning models are briefly explained below.

InceptionV3 which is indicated as a GoogleNet architecture, represents one of the pre-trained CNN models devoted for classification. This model includes forty-eight deep layers and utilizes the modules of inception that need a connected layer with the convolutions of 1×1, 3×3, and 5×5. In this model, the number of non-trainable parameters is 54,528 and the number of trainable parameters is 20,806,952. The summarized baseline of InceptionV3 model architecture is demonstrated in Table 3.

EfficientNetV2 is a pre-trained CNN model (includes an inverted residual block (MBConv) and Fused-MBConv) which is concentrated on providing fewer parameters and higher accuracy. It is a smaller model with higher parameter effectiveness, and faster training speed than the first version. In this model, the obtained number of non-trainable parameters is 512,576 and the obtained number of trainable parameters is 117,234,272. The summarized baseline of EfficientNetV2 model architecture is demonstrated in Table 4.

Table 3. InceptionV3 Model Architecture for Covid-19 discrimination

Layer	Output Shape	Parameters (P_s)
Input	"_, 224, 224, 3"	-
InceptionV3(Functional)	"_, 7, 7, 2048"	20861480
Global Average Pooling 2D	"_, 2048"	-
Dropout	"_, 2048"	-
Dense	"_, 3"	2049

Trainable P_s: 20,806,952
Non-trainable P_s: 54,528
Total P_s: 20,863,529

Table 4. EfficientNetV2 Model Architecture for Covid-19 discrimination

Layer	Output Shape	Parameters (P_s)
Input	"_, 224, 224, 3"	-
EfficientNetV2(Functional)	"_, 7, 7, 1280"	117746848
Global Average Pooling 2D	"_, 1280"	-
Dense	"_, 3"	3843

Trainable P_s: 117,234,272
Non-trainable P_s: 512,576
Total P_s: 117,746,848

Tables 5, 6, and 7 present an overall comparison for the performances of the models using the COVID-19 Radiography dataset. It can be noticed that the highest level of performance was attained by the proposed deep CNN model, which has reached up to a 99.998% accuracy, 99.8% precision, 99.9% F1-score, and 100% recall. These results indicate that the novel proposed model predicts the whole cases of COVID-19 correctly. Moreover, the EfficientNetV2 model has conducted a higher performance in detecting normal, viral-pneumonia, and COVID-19 pneumonia cases with respect to the InceptionV3 model. Figures 3, 4, and 5 show the confusion matrices for the implemented models.

The evaluated results using the proposed deep CNN model, for COVID-19 versus normal versus viral-pneumonia cases are shown on figure 3. According to these evaluated results, 723 COVID-19 cases are classified properly and only one case is classified wrongly as viral-pneumonia. Across the normal cases, 2038 cases were detected correctly and only 1 case was misclassified as COVID-19, while all the viral-pneumonia cases were classified successfully without any misclassification. It is

Table 5. Performance evaluation of novel proposed deep CNN model

	Precision Metric	Recall Metric	F1-score Metric	Support
COVID-19	0.998	0.999	0.999	724
NORMAL	0.999	0.998	0.998	2039
Viral-pneumonia	1.0	1.0	1.0	269
Accuracy	0.999			3032
Macro-average	0.999	0.998	0.997	3032
Weight-average	0.998	0.1	0.999	3032

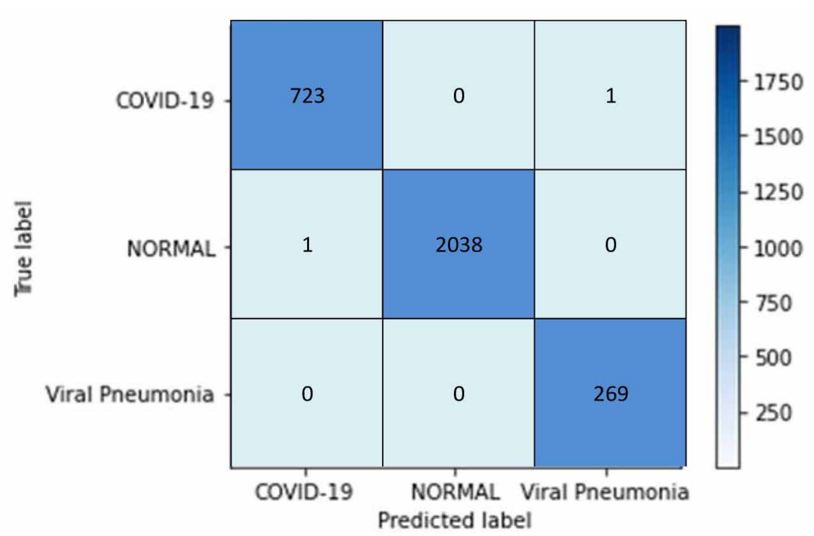
Table 6. Performance evaluation of InceptionV3 model

	Precision Metric	Recall Metric	F1-score Metric	Support
COVID-19	0.88	0.79	0.83	724
NORMAL	0.91	0.96	0.93	2039
Viral-pneumonia	0.93	0.85	0.89	269
Accuracy	0.91			3032
Macro-average	0.91	0.86	0.88	3032
Weight-average	0.91	0.91	0.91	3032

Table 7. Performance evaluation of EfficientNetV2 model

	Precision Metric	Recall Metric	F1-score Metric	Support
COVID-19	0.94	0.81	0.87	724
NORMAL	0.93	0.98	0.95	2039
Viral-pneumonia	0.93	0.87	0.90	269
Accuracy	0.93			3032
Macro-average	0.93	0.89	0.91	3032
Weight-average	0.93	0.93	0.93	3032

Figure 3. Confusion Matrix of proposed deep CNN model



noteworthy that the proposed model has classified with 99% accuracy the COVID-19 cases from the set of testing, which is very important in the context of medical disease detection. In Figure 4, it is also observed that 570, 1952, and 228 concerning COVID-19, normal, and viral-pneumonia cases, are respectively classified properly using the InceptionV3 model. It is shown on Figure 5 that, 584,

Figure 4. Confusion Matrix of InceptionV3 model

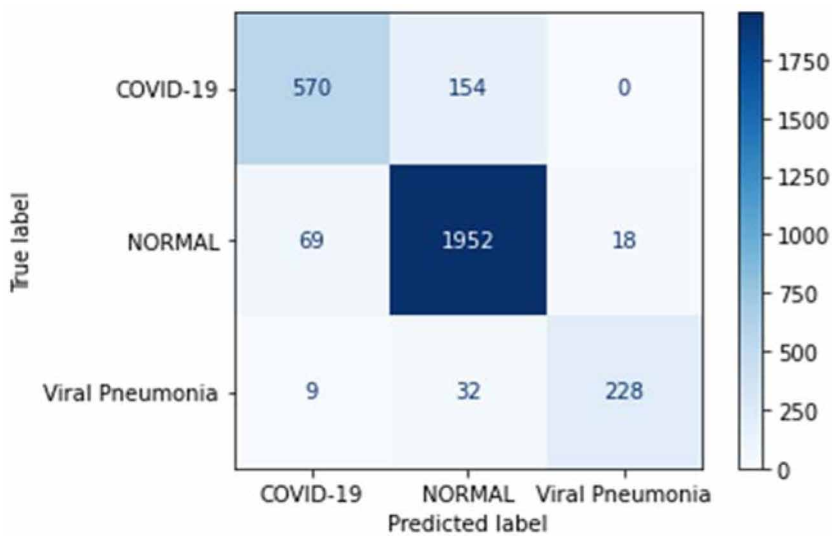
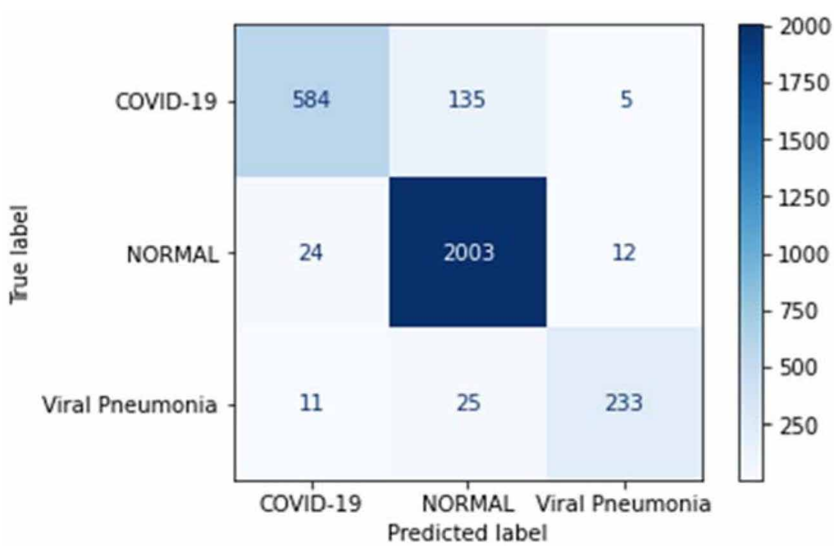


Figure 5. Confusion Matrix of EfficientNetV2 model

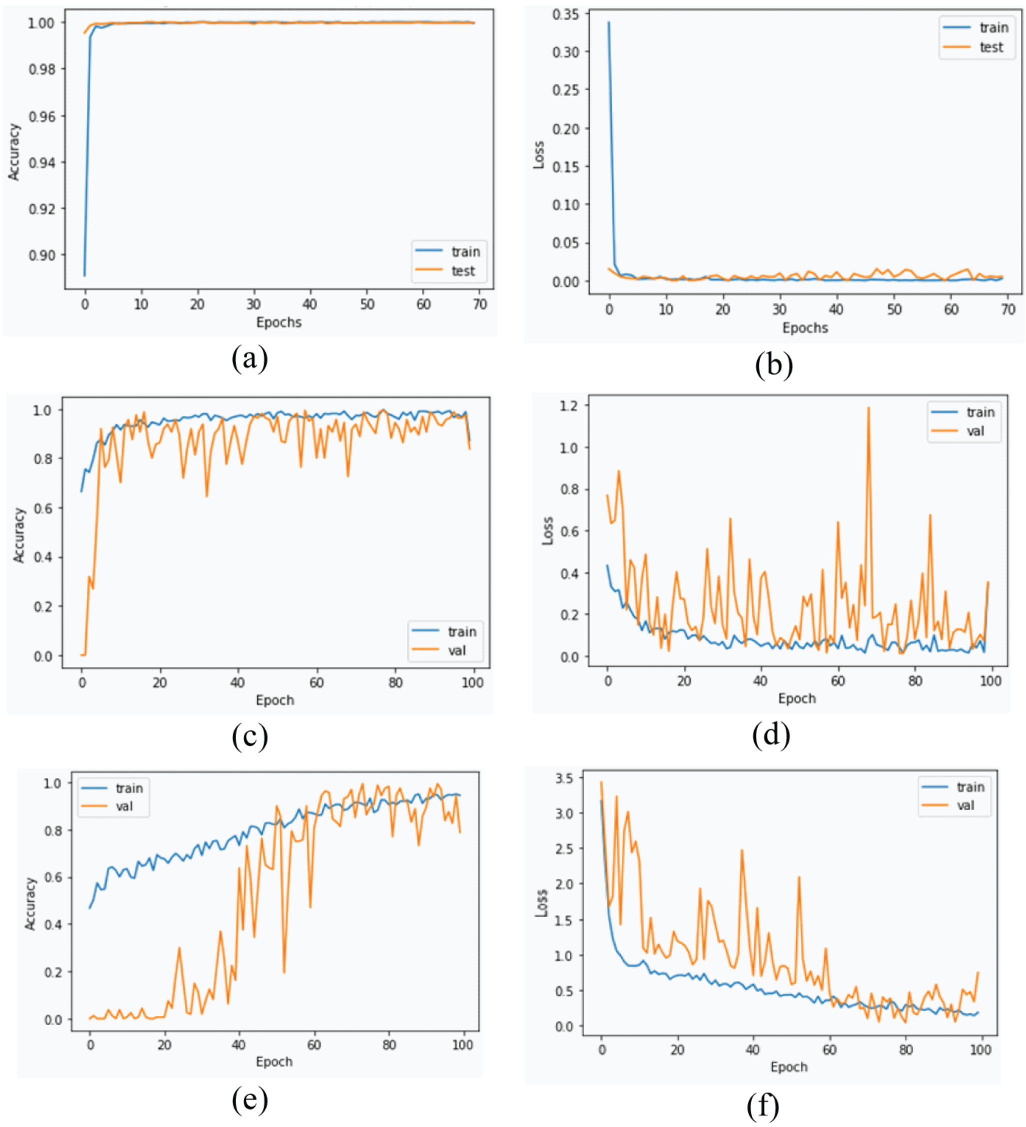


2003, and 233 concerning COVID-19, normal, and viral-pneumonia cases, are respectively classified properly using EfficientNetV2 model.

For more investigation on overfitting behaviors of the models, the obtained results for accuracy, loss concerning validation and training learning per epoch are shown in Figure 6. In contrast to the pre-trained models, there is no overfitting in the performance of the proposed deep CNN model owing to the small differences between the loss and accuracy concerning the sets of validation and training.

Table 8 demonstrates a comparison between the performance of three implemented models and various recently existing models of deep learning utilized for detecting COVID-19. This

Figure 6. The curves of accuracy and loss concerning validation and training learning per epoch for the proposed developed deep CNN model in (a) and (b), respectively, for the InceptionV3 model in (c) and (d), respectively, and for the EfficientNetV2 model in (e) and (f), respectively



comparison depicts the effectiveness of the proposed deep CNN model in discriminating COVID-19 from typical pneumonia.

CONCLUSION

It can be said that the present pandemic has changed human life to an exceptional extent. However, the research community efforts have been immense on different fronts, and in this direction, it is shown in this work that, the novel proposed deep learning CNN model has attained a competitive performance with InceptionV3 model, EfficientNetV2 model and other models in the literature. The effective novel proposed three-class deep CNN model which is used to discriminate between

Table 8. Comparison of the proposed model and the other implemented pre-trained models with the state-of-the-art models

Author(s), Year	Subjects	Models	Precision Metric	Recall Metric	F1-score Metric	Accuracy Metric
Chowdhury et al., 2020	1579 Normal, 423 COVID-19, and 1485 Viral-pneumonia	DenseNet201 based Transfer Learning Model	97.95%	97.94%	97.94%	97.94%
Arifin et al., 2021	1341 Normal, 219 COVID-19, and 1345 Viral-pneumonia	SSD MobileNetV1	-	-	-	94%
Yadanar Win et al., 2021	10,192 Normal, 3616 COVID-19, and 1345 Viral-pneumonia	Ensemble Classifier of Best Models	-	99.27%	98.3%	99.23%
Khan et al., 2022	10,192 Normal, 3616 COVID-19, 1345 Viral-pneumonia, and 6012 Lung Opacity	EfficientNetB1	97.25%	96.50%	97.50%	96.13%
Aslan et al., 2022	1341 Normal, 219 COVID-19, and 1345 Viral-pneumonia	DenseNet201 model and Support Vector Machine	96.42%	96.42%	96.41%	96.29%
Proposed Model	10,192 Normal, 3616 COVID-19 and 1345 Viral-pneumonia	Developed CNN Model	99.8%	100%	99.9%	99.998%
Pre-trained Models	10,192 Normal, 3616 COVID-19 and 1345 Viral-pneumonia	InceptionV3	91%	91%	91%	91%
		EfficientNetV2	93%	93%	93%	93%

Covid-19 and typical pneumonia has achieved 99.998% accuracy, 100% recall, 99.8% precision, and 99.9% F1-score. Accordingly, it is shown that, this model is more reliable and robust in successfully detecting COVID-19 cases. And this novel proposed method enables itself to be a perfect candidate for specifying COVID-19 from the images of chest X-rays. This presented work can be expanded in the future by utilizing larger datasets with more than three classes to be discriminated. Additionally, innovative techniques for hyper-parameter tuning and feature extraction can be applied to improve the model performance. Furthermore, optimization algorithms, especially nature-inspired algorithms, can be utilized for choosing the preferable features to be classified.

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