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Article

Multi-Classification Network for Identifying COVID-19 Cases Using Deep Convolutional Neural Networks

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Abstract: The novel coronavirus 2019 (COVID-19) rapidly spreading around the world and turns into a pandemic situation, consequently, detecting the coronavirus (COVID-19) affected patients are now the most critical task for medical specialists. The deficiency of medical testing kits leading to huge complexity in detecting COVID-19 patients worldwide, resulting in the number of infected cases is expanding. Therefore, a significant study is necessary about detecting COVID-19 patients using an automated diagnosis method, which hinders the spreading of coronavirus. In this paper, the study suggests a Deep Convolutional Neural Network-based multi-classification framework (COV-MCNet) using eight different pre-trained architectures such as VGG16, VGG19, ResNet50V2, DenseNet201, InceptionV3, MobileNet, InceptionResNetV2, Xception which are trained and tested on the X-ray images of COVID-19, Normal, Viral Pneumonia, and Bacterial Pneumonia. The results from 4-class (Normal *vs.* COVID-19 *vs.* Viral Pneumonia *vs.* Bacterial Pneumonia) demonstrated that the pre-trained model DenseNet201 provides the highest classification performance (accuracy: 92.54%, precision: 93.05%, recall: 92.81%, F1-score: 92.83%, specificity: 97.47%). Notably, the DenseNet201 (4-class classification) pre-trained model in the proposed COV-MCNet framework showed higher accuracy compared to the rest seven models. Important to mention that the proposed COV-MCNet model showed comparatively higher classification accuracy based on the small number of pre-processed datasets that specifies the designed system can produce superior results when more data become available. The proposed multi-classification network (COV-MCNet) significantly speeds up the existing radiology based method which will be helpful for the medical community and clinical specialists to early diagnosis the COVID-19 cases during this pandemic.

Keywords: COVID-19; chest X-ray images; deep convolutional neural network; COV-MCNet; deep learning

1 Introduction

In recent times, we have all been hit by the new scare called the “Novel Corona Virus (COVID-19)”. Many people all over the world are dying and getting infected with this virus. According to the World Health Organization (WHO), there is a total of 41,570,883 confirmed cases, 1,134,940 deaths, and 31,282,596 recoveries globally in almost 235 countries (as of October 23, 2020) [1]. This is a recently discovered species in the large coronavirus family [2]. To date (October 23, 2020), there is no known cure or vaccine for the virus. One big challenge in the combat of the pandemic has been the limited number of medical equipment for rapid COVID-19 testing, Real-time Reverse Transcription Polymerase Chain

Reaction (RT-PCR) has emerged as one of the most widely used techniques for coronavirus testing [3]. In the primary diagnosis and treatment of this virus, chest radiological imaging such as computed tomography (CT) and X-rays have significant functions that can help radiologists detect the virus [4]. RT-PCR test kits have been in great scarcity since the outbreak of COVID-19. As a consequence, it is not possible to screen and isolate several suspicious patients in time, resulting in them transmitting the disease unknowingly. New individuals infected with coronavirus may develop mild to severe respiratory disease, in some cases, carriers of the virus show no symptoms at all, this refers to the asymptomatic patients. Both animals and humans can be infected by coronavirus disease. The first case was recorded in Wuhan, the capital of the Hubei Province of China, in December 2019, after which it eventually spread across the globe. Coronavirus is a large family of viruses called Coronaviridae with Extreme Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS) in several other animals [5]. The SARS coronavirus (SARS-CoV) was first identified and recognized in February 2003, although cases were traced to November 2002. It is thought to be an animal virus, possibly from bats, that infected persons in Southern China, Guangdong Province. During the 2003 epidemic, nearly 8,000 people worldwide got infected as it spread to 26 countries, leaving 774 people dead. After SARS, the first known cases of MERS occurred in April 2012. MERS symptoms were fever, cough, and shortness of breath. MERS reached 27 countries by September 2012 with over 800 deaths. 80% of the reported MERS cases were in Saudi Arabia [6]. Dry cough, fever, difficulty in breathing, and tiredness are the most common symptoms of coronavirus, in the advanced stage of the virus, there are respiratory complications such as pneumonia, kidney disease, and lung fluid growth. COVID-19 has similar symptoms with the other known coronaviruses but the new virus spreads at a faster rate. As of October 23, 2020, Fig. 1 indicates the overall rising number of cases of COVID-19 worldwide.

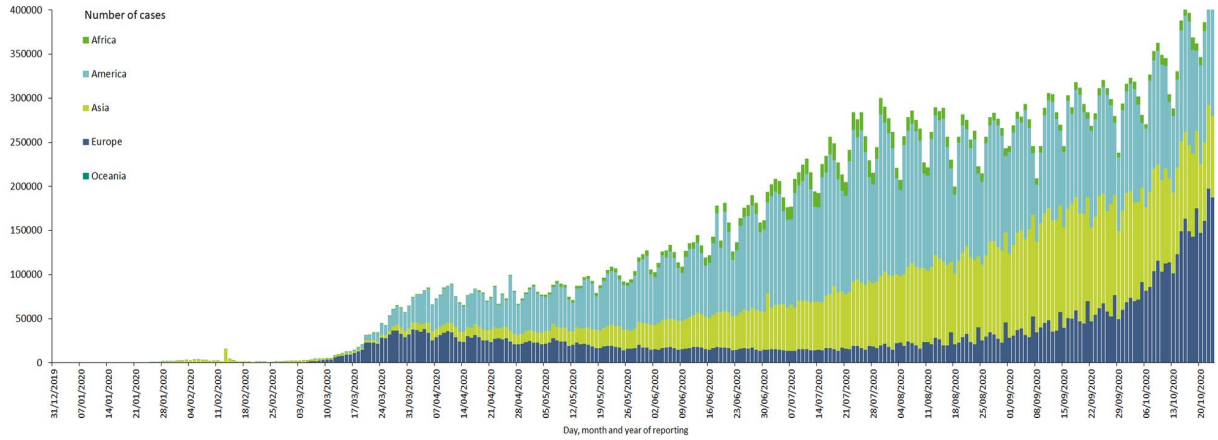

Figure 1: Cumulative COVID-19 cases worldwide, as of 23 October 2020 (according to the applied case definition and testing strategies in the affected countries)

The serial interval of COVID-19 is estimated to be 5–6 days, which is similar and lower than the serial interval of Extreme Acute Respiratory Syndrome (SARS) and lower than its median incubation time [7]. Fan et al. classified infected regions using chest CT images, based on a new COVID-19 Lung Infection Segmentation Deep Network (Inf-Net) [8]. In this research [9], Waheed et al. developed an Auxiliary Classifier Generative Adversarial Network (ACGAN) based model called CovidGAN to generate synthetic chest X-ray (CXR) images.

In this time of the rapid spread of COVID-19, several kinds of research have been suggested [10–15]. PCR tests and CT scans are comparatively expensive for all screening procedures [16] and sometimes more selective tests are needed and often necessary for vital patients. X-ray imaging is comparatively cost-effective and commonly used for diagnosis or segmentation of lung infections and often convenient

for diagnosis of COVID-19 as well as [17]. Wang et al. study presented Artificial Intelligence's based deep learning methods to extract COVID-19's specific graphical features [18]. The infection with COVID-19 is serious enough to be called acute respiratory distress syndrome (ARDS) rather than SARS and MERS. It is usually estimated that most infectious patients are genetically stable CoV carriers and that these viruses are the primary cause for around 15% to 20% of acute respiratory infections [19].

Due to the lack of a diagnostic system anywhere, which raises fear among people, COVID-19 testing has recently become a difficult activity. We need to rely on other diagnostic procedures because of the significant shortage of COVID-19 testing kits. Since COVID-19 targets the epithelial cells that impact our lung area, to analyze health, medical specialists can use X-ray images of the lungs of a patient. In detecting pneumonia, lung inflammation boils, and/or other health problems medical doctors usually use X-ray images. And almost all hospitals have X-ray imaging equipment, although often it may be hard to use X-ray imaging in some environments. Without the enthusiastic test kits, it would be feasible to use X-ray to research for COVID-19. Again, a downside is that an X-ray test needs a specialist in radiology for examination, and this takes some time. Therefore, to time, it is necessary to develop an automated research process.

In this study, we implement a deep convolutional neural network (CNN)-based automated classification system for identifying COVID-19 infected cases from chest radiology images. The proposed network is called COV-MCNet combining with different pre-trained models that classify three types of pneumonia; COVID-19, Viral Pneumonia, and Bacterial Pneumonia. The proposed system was implemented for 4-class (Normal, COVID-19, Viral Pneumonia, and Bacterial Pneumonia) classification using eight pre-trained models (VGG16, VGG19, ResNet50V2, InceptionV3, InceptionResNetV2, DenseNet201, MobileNet, and Xception). The proposed network produced promising results, even though using a small dataset (300 Normal, 240 COVID-19, 300 Viral Pneumonia, and 300 Bacterial Pneumonia).

2 Materials and Methods

2.1 Dataset

This study has used a total of 1140 images (240 COVID-19, 300 Normal, 300 Viral Pneumonia, and 300 Bacterial Pneumonia) to develop the multi-classification network (COV-MCNet). The COVID-19 X-ray images are sourced from the GitHub repository [20] and the rest three dataset (Normal, Viral Pneumonia, and Bacterial Pneumonia) were obtained from the Kaggle repository [21]. Therefore, these datasets have been used for feature extraction based on different deep learning architectures. Details of the used dataset as shown in Tab. 1. Since this study focused primarily on the detection of COVID-19 infected cases, therefore, the MERS, SARS, and ARDS virus images were not considered. The two datasets are examined separately in the COV-MCNet proposed models. Fig. 2 shows several chest X-ray images of Normal, COVID-19, Viral Pneumonia, and Bacterial Pneumonia patients.

Table 1: Details of dataset used in the present study

Classification task	Classes	Number of datasets
4-class classification	Normal, COVID-19, Viral Pneumonia, Bacterial Pneumonia	300 Normal, 240 COVID-19, 300 Viral Pneumonia, 300 Bacterial Pneumonia

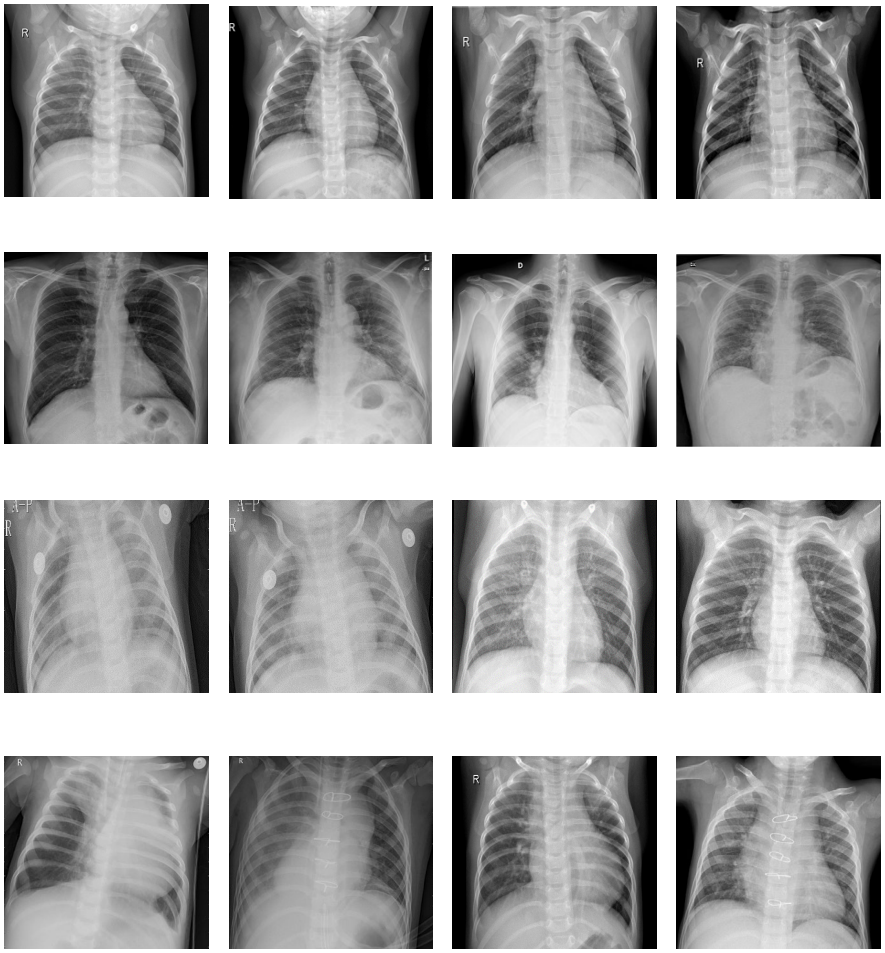

Figure 2: Samples of prepared dataset (a) Normal (b) COVID-19 (c) Viral Pneumonia (d) Bacterial Pneumonia

2.2 Proposed COV-MCNet

Deep learning methods are widely used in a variety of studies such as image classification, segmentation, and skin disease detection of medical statistics [22,23]. The study proposed a state-of-the-art deep learning image classifier, namely COV-MCNet (Multi-classification network) based on a deep convolutional neural network (CNN). The COV-MCNet uses eight different pre-trained models which are assembled into 4-classes to classify COVID-19, Normal, Viral Pneumonia, and Bacterial Pneumonia cases. The entire methodology is divided into three steps: input and pre-processing steps, pre-trained models, and finally training and classification process. ImageNet is an image database with over 14 million images belonging to over 20 thousand categories created for image recognition competitions [24]. The VGG16 and VGG19 [25] model is an improved version of the convolutional neural network (CNN). These models have small convolution filters (3 × 3) to get a deeper and more complex network. These two models differ in the depth of convolution, pooling, and fully connected layers. The ResNet50V2 [26] is the upgrade version of ResNet50. The ResNet50V2 model has Deep Residual Networks, which is eight times deeper compared to the VGG nets. This architecture is based on skip connection, which allows us to take activation from one layer and feed it to the future layer. InceptionV3 [27] aims to utilize the additional computation as competently as likely by appropriately factorized convolutions and aggressive regularization. The model 48 layers deep along with pooling and fully connected layers. Inception-ResNet-v2 [28] is the mutual architecture of the Inception with residual connections. This architecture is

164 layers deep. As a result, the network has erudite rich feature demonstrations for an extensive range of images. DenseNet201 (Densely Connected Convolutional Networks) [29] has 201 layers on the ImageNet dataset and it has some compelling advantages: They improve the vanishing-gradient difficulty, fortify feature propagation, boost feature reuse, and significantly reduce the number of parameters. MobileNet [30] is an effective model for mobile and entrenched vision applications. This model uses depthwise separable convolutions based on a rationalized architecture to build lightweight deep neural networks. Xception [31] is a 71 layers deep convolutional neural network architecture enthused by Inception, where Inception modules have been substituted with depthwise distinguishable convolutions. The network trained on more than a million images from the ImageNet database. A schematic representation of the proposed network is shown in Fig. 3.

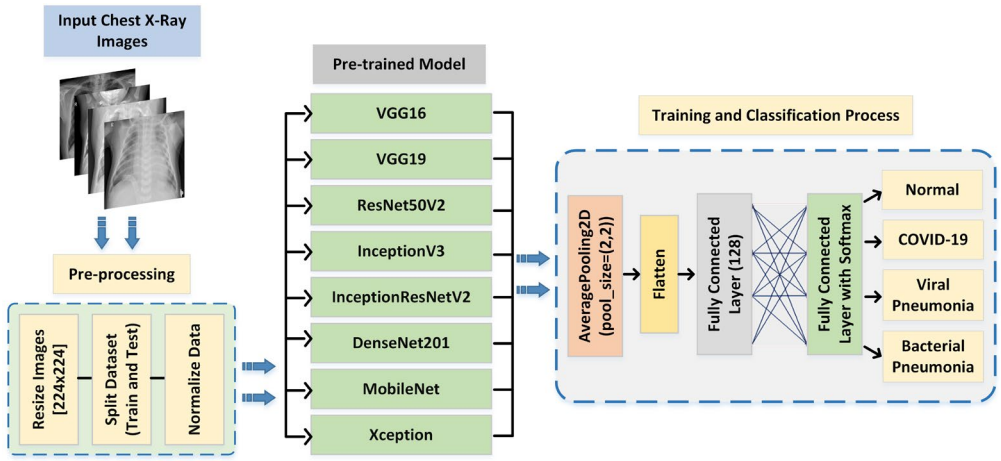

Figure 3: Graphical workflow of proposed COV-MCNet framework for the detection of Normal, COVID-19, Viral Pneumonia and Bacterial Pneumonia patients

2.2.1 Input and Pre-Processing Steps

Since the properties of the image (width and height) vary for chest X-ray images of Normal, COVID-19, Viral Pneumonia, and Bacterial Pneumonia, therefore, the study has used a fixed size of 224 × 224 pixels. Following that, 80% of the data are used as the training dataset and 20% of them are used to evaluate the trained model. Finally, to obtain the decimal values (0 to 1), we normalized the data by dividing 255.

2.2.2 Pre-Trained Models

Pre-trained models are trained on a large benchmark dataset as a starting point to solve different problems. In this study, eight different pre-trained models (e.g., VGG16, VGG19, ResNet50V2, InceptionV3, InceptionResNetV2, DenseNet201, MobileNet, and Xception) have been used for multi-classification (4-class). All the models have different convolution and pooling layers which extract the features from images and classifier categorize the images from extracted features.

2.2.3 Training and Classification Process

In the final step, we fine-tuned the pre-trained models with deep learning image classifiers for detecting COVID-19, Normal, Viral Pneumonia, and Bacterial Pneumonia cases. In the training and classification process, AveragePooling2D have used for all the models to calculate the average for each patch of the feature map with pool size (2, 2). Afterward, we flattened the activations to create a vectorized feature map and connected two fully connected layers; one layer contained 128 nodes, and the other consisted of 4 for 4-class classification. Subsequently, the activations from the second fully

connected layer were fed into a softmax layer, which provided the probability for each of Normal, COVID-19, Viral Pneumonia, and Bacterial Pneumonia.

2.3 Experimental Setup

Python programming language was used for the experiments to training the proposed COV-MCNet framework and Jupyter Notebook as an editor for executing the codes. The background running environment is built-up using deep learning framework TensorFlow (1.14) and Keras package [32]. All experiments were carried out on CPU Intel Core i7 9700K–(32 GB/2 TB HDD/128 GB SSD/Windows 10 Home/4 GB Graphics) and equipped with GPU NVIDIA GeForce RTX 2080Ti. The COV-MCNet framework was trained with random initialization weights using the SGD (Stochastic Gradient Descent) optimizer. The batch size and learning rate are experimentally set to 10, 0.0001, and the number of epochs is set to 20 to avoid overfitting for all experiments.

2.4 Performance Metrics

To test the classification performance of pre-trained models in the COV-MCNet, the following metrics have been implemented in this study to show the classified or misclassified cases. The performance metrics are calculated based on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values.

2.4.1 Accuracy

It measures the ratio of correctly classified cases concerning the whole dataset. If the accuracy is higher, that means the models perform better. The accuracy is a portion of the predicted or classified value to its actual value. It represented as follows:

$$\mathrm{Acc} = \frac{\mathrm{TN} + \mathrm{TP}}{\mathrm{TN} + \mathrm{TP} + \mathrm{FN} + \mathrm{FP}}, \tag{1}$$

2.4.2 Precision

It measures the percentage of correctly classified as positive out of all positive cases. It is defined as follows:

$$\mathrm{Pre} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \tag{2}$$

2.4.3 Recall

The recall is computed as the ratio of positives that were correctly predicted as true positives divided by the number of actual positives. It is calculated as follows:

$$\mathrm{Rec} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \tag{3}$$

2.4.4 F1-Score

F1 Score is calculated based on the scores of precision and recall. It provides the classification capability of the model. F1 score measures the test's accuracy. If the F1 score presents the best value, that means perfect precision and recall. It is calculated as follows:

$$\mathrm{F1} - \mathrm{S} = 2 \times \left(\frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}\right), \tag{4}$$

2.4.5 Specificity

It is also called True Positive Rate (TPR) which measures the ratio of actual negatives that are correctly labeled. It is represented as follows:

$$\text{Spe} = \frac{\text{TN}}{\text{TN} + \text{FP}}, \tag{5}$$

TP is the proportion of positive cases that are correctly classified as positive; FP is the proportion of negative cases that are misclassified as positive; TN is the proportion of negative that is correctly classified as negative and FN is the proportion of positive that is misclassified as negative by the proposed model.

3 Results and Discussion

3.1 4-Class ClassificationTraining, and Validation Accuracy and Loss

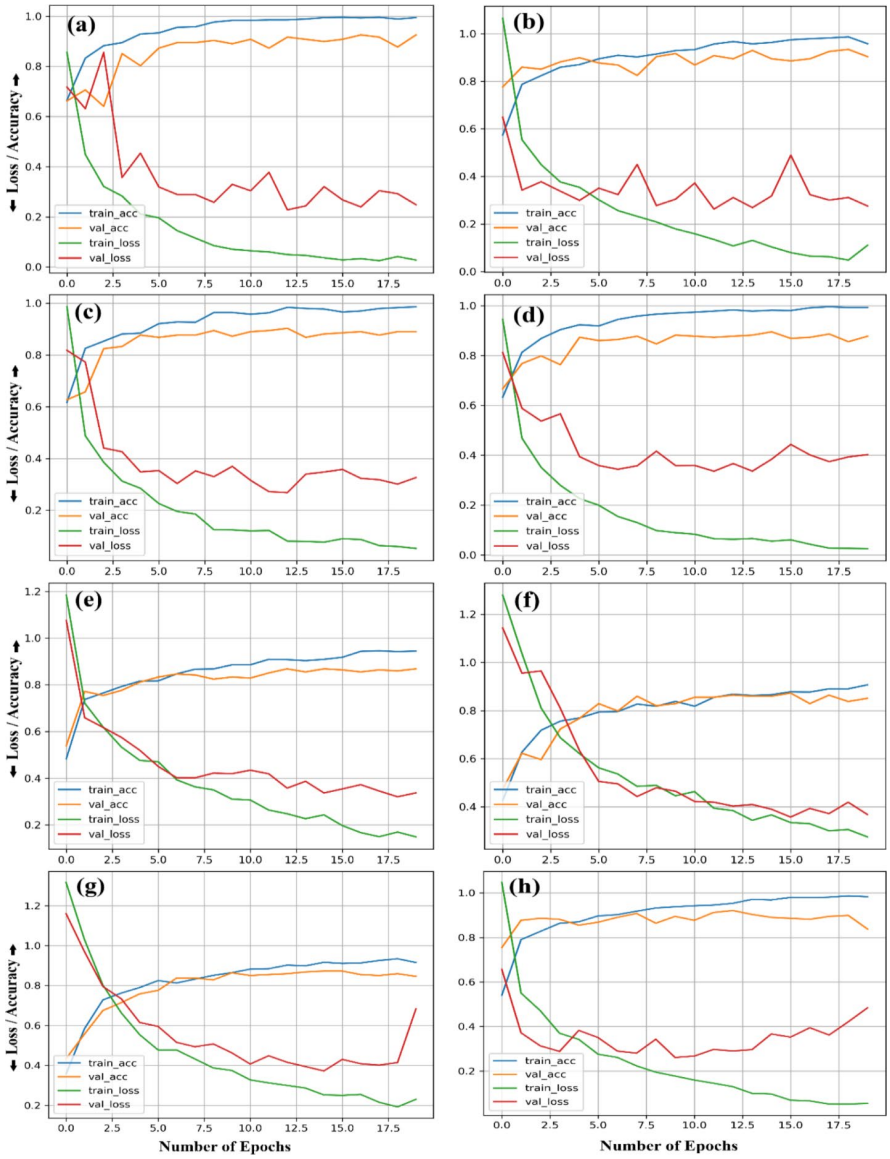

Figure 4: The training accuracy (train_acc), loss (train_loss) and validation accuracy (val_acc), loss (val_loss) curves of all pre-trained models in the COV-MCNet for 4 classes: a) DenseNet201, b) VGG16, c) MobileNet, d) ResNet50V2, e) InceptionV3, f) Xception, g) InceptionResNetV2, and h) VGG19

Fig. 4 shows the training and validation accuracy with their loss values for the 4-class classification based on the eight pre-trained models (DenseNet201, VGG16, MobileNet, ResNet50V2, InceptionV3, Xception, InceptionResNetV2, and VGG19). The training time for all pre-trained models has been conducted up to the 20th epoch to avoid overfitting. The DenseNet201 model (Fig. 4a) showed the highest validation accuracy (92.54%) compared to the VGG16 (90.35%) (Fig. 4b), MobileNet (89.04%) (Fig. 4c), ResNet50V2 (87.72%) (Fig. 4d), InceptionV3 (86.84%) (Fig. 4e), Xception (85.09%) (Fig. 4f), InceptionResNetV2 (84.65%) (Fig. 4g), and VGG19 (83.77%) (Fig. 4h). The evaluation outputs of the best performance model (DenseNet201) for 4-class classification are shown in Figure S1. Moreover, loss values exhibited a greater variation at the beginning of the training for all the eight pre-trained models, which may be due to using the less number of COVID-19 datasets as compared to the other three datasets (Normal, Viral Pneumonia, and Bacterial Pneumonia) (Fig. 4). To the best of our knowledge, there are only two studies about 4-class classification were found based on CoroNet Xception and COVID-Net. For example, Khan et al. [33] detected COVID-19 cases based on the CoroNet Xception pre-trained model and reported an accuracy of 89.6%. In contrast, Wang et al. [34] proposed a deep neural network-based model, namely COVID-Net, they achieved 92.4% accuracy. In comparison to these studies, the DenseNet201 model in our proposed network (COV-MCNet) showed high accuracy than Khan et al. [33] and comparable accuracy with Wang et al. [34].

3.2 The 4-Class Classification Confusion Matrix and ROC Curve

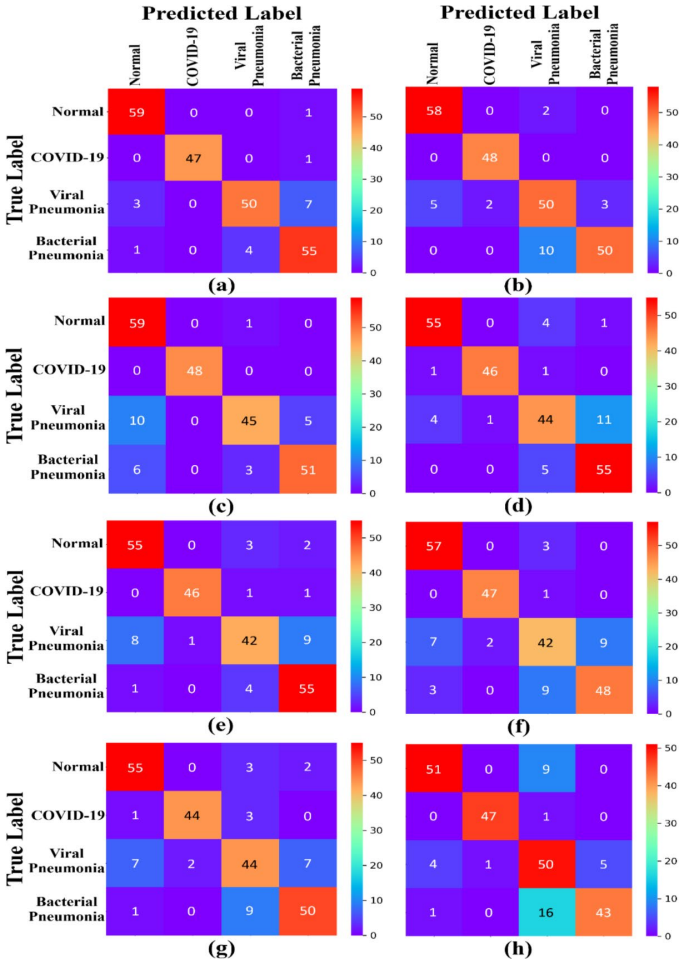

Figure 5: The confusion matrix results of 4-class classification obtained using pre-trained models in the COV-MCNet: a) DenseNet201, b) VGG16, c) MobileNet, d) ResNet50V2, e) InceptionV3, f) Xception, g)

InceptionResNetV2, and h) VGG19. Here, the diagonal red, light orange, and dark orange are true positive (TP), and the light and dark blue, cyan is the miss classifications of our model

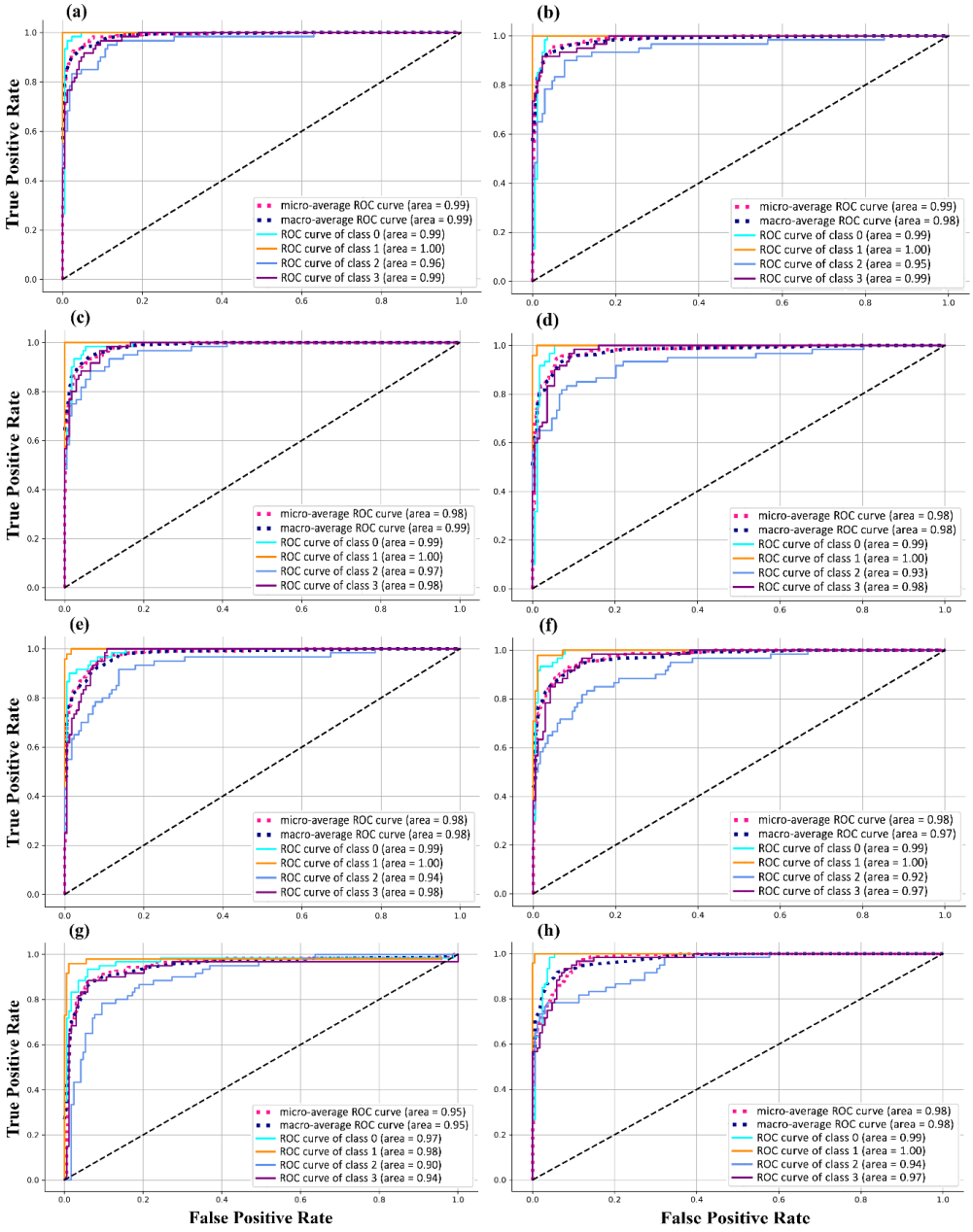

Figure 6: ROC Curve of pre-trained models for 4-class classification in the COV-MCNet: (Class 0: Normal, Class 1: COVID-19, Class 2: Viral Pneumonia, Class 3: Bacterial Pneumonia). a) DenseNet201, b) VGG16, c) MobileNet, d) ResNet50V2, e) InceptionV3, f) Xception, g) InceptionResNetV2, and h) VGG19

Figs. 5 and 6 show the confusion matrix (CM) and the receiver operating characteristic curve (ROC) for the 4-class classification problem, respectively. Rows of the confusion matrix correspond to an actual class while columns represent to the predicted class and the color intensity specifies the probability of each element in a row. The results (Fig. 5) show that the pre-trained models classified COVID-19 cases better than other classes of Normal, Viral Pneumonia, and Bacterial Pneumonia. Besides, the roc curve (Fig. 6) plots the TPR against FPR which measures the classification performance on the various

threshold. In Fig. 6a, AUC~1.00 represents COVID-19 (i.e., Class 1), AUC~0.99 represents normal (Class 0), AUC~0.97 represents Viral Pneumonia (Class 2) 0.97, and AUC~0.98 represents Bacterial Pneumonia (Class 3).

3.3 4-Class Comparative Performance Metrics of Pre-Trained Models in the COV-MCNet

Tab. 2 demonstrates the performance metrics of the eight pre-trained models used in the proposed network for 4-class classification. It can be noticed that the DenseNet201 model showed the best classification performance for each class such as Normal (Precision: 93.65%, Recall: 98.33%, F1-Score: 95.93%, Specificity: 97.62%), COVID-19 (Precision: 100%, Recall: 97.92%, F1-Score: 98.95%, Specificity: 100%), Viral Pneumonia (Precision: 92.59%, Recall: 83.33%, F1-Score: 87.72%, Specificity: 97.62%), Bacterial Pneumonia (Precision: 85.94%, Recall: 91.67%, F1-Score: 88.71%, Specificity: 94.64%). As the DenseNet201 model classifier uses features of all complexity levels which inclines to provide further smooth decision boundaries. Also, it has comparatively more layers (i.e., 201 layers) than the rest models as well as improves the vanishing-gradient difficulty, fortify feature propagation, and boost feature reuse, which significantly reduces the number of parameters. Therefore, these results recommended that the DenseNet201 model is robust and superior to the other tested models in terms of precision, recall, F1-score, and specificity.

Table 2: The performance metrics of eight pre-trained models for 4-class are presented based on Precision (Pre), Recall (Rec), F1-score (F1-S), Specificity (Spe) values

Models	Classes	TP	TN	FP	FN	Pre	Rec	F1-S	Spe
DenseNet201	Normal	59	164	4	1	93.65	98.33	95.93	97.62
	COVID-19	47	180	0	1	100	97.92	98.95	100
	Viral Pneumonia	50	164	4	10	92.59	83.33	87.72	97.62
	Bacterial Pneumonia	55	159	9	5	85.94	91.67	88.71	94.64
VGG16	Normal	58	163	5	2	92.06	96.67	94.31	97.02
	COVID-19	48	178	2	0	96	100	97.96	98.89
	Viral Pneumonia	50	156	12	10	80.65	83.33	81.97	92.86
	Bacterial Pneumonia	50	165	3	10	94.34	83.33	88.49	98.21
MobileNet	Normal	59	152	16	1	78.67	98.33	87.41	90.48
	COVID-19	48	180	0	0	100	100	100	100
	Viral Pneumonia	45	164	4	15	91.84	75	82.57	97.62
	Bacterial Pneumonia	51	163	5	9	91.07	85	87.93	97.02
ResNet50V2	Normal	55	163	5	5	91.67	91.67	91.67	97.02
	COVID-19	46	179	1	2	97.87	95.83	96.84	99.44
	Viral Pneumonia	44	158	10	16	81.48	73.33	77.19	94.05
	Bacterial Pneumonia	55	156	12	5	82.09	91.67	86.62	92.86
InceptionV3	Normal	55	159	9	5	85.94	91.67	88.71	94.64
	COVID-19	46	179	1	2	97.87	95.83	96.84	99.44
	Viral Pneumonia	42	160	8	18	84	70	76.36	95.24
	Bacterial Pneumonia	55	156	12	5	82.09	91.67	86.62	92.86
Xception	Normal	57	158	10	3	85.07	95	89.76	94.05
	COVID-19	47	178	2	1	95.92	97.92	96.91	98.89
	Viral Pneumonia	42	155	13	18	76.36	70	73.04	92.26
	Bacterial Pneumonia	48	159	9	12	84.21	80	82.05	94.64
InceptionResNetV2	Normal	55	159	9	5	85.94	91.67	88.71	94.64
	COVID-19	44	178	2	4	95.92	91.67	93.75	98.89

	Viral Pneumonia	44	153	15	16	74.58	73.33	73.95	91.07
	Bacterial Pneumonia	50	159	9	10	84.75	83.33	84.03	94.64
VGG19	Normal	51	163	5	9	91.07	85	87.93	97.02
	COVID-19	47	179	1	1	97.92	97.92	97.92	99.44
	Viral Pneumonia	50	158	10	10	83.33	83.33	83.33	94.05
	Bacterial Pneumonia	43	163	5	17	89.58	71.67	79.63	97.02

It is observed from Tab. 3, the DenseNet201 pre-trained model in the proposed study (COV-MCNet) showed better results in detecting COVID-19 for 4-class with accuracy, precision, recall, F1-score, and specificity are 92.54%, 93.05%, 92.81%, 92.83%, and 97.47%, respectively.

Table 3: Accuracy (Acc), Precision (Pre), Recall (Rec), F1-Score (F1-S), and Specificity (Spe) results of all the pre-trained models used in COV-MCNet for 4-class classification (Normal *vs.* COVID-19 *vs.* Viral Pneumonia *vs.* Bacterial Pneumonia)

Classification models	Performance metrics (%)				
	Acc	Pre	Rec	F1-S	Spe
DenseNet201	**92.54**	**93.05**	**92.81**	**92.83**	**97.47**
VGG16	90.35	90.76	90.83	90.68	96.75
MobileNet	89.04	90.40	89.58	89.48	96.28
ResNet50V2	87.72	88.28	88.13	88.08	95.84
InceptionV3	86.84	87.48	87.29	87.13	95.55
Xception	85.09	85.39	85.73	85.44	94.96
InceptionResNetV2	84.65	85.30	85	85.11	94.81
VGG19	83.77	90.48	84.48	87.20	96.88

4 Conclusions

As the COVID-19 cases are still increasing daily, quick identification of COVID-19 patients is can be one of the effective steps towards preventing the spread of the virus into the non-affected community. Thus and so, this study has proposed a multi-classification approach, namely COV-MCNet based on eight different pre-trained models (VGG16, VGG19, ResNet50V2, InceptionV3, InceptionResNetV2, DenseNet201, MobileNet, and Xception) to detect COVID-19 patients automatically. The suggested models could successfully detect the COVID-19 infected cases based on the 4-class classification. The 4-class classification demonstrated the DenseNet201 best classification model of COVID-19 infected cases with an accuracy of 92.54%. The study achieved promising results in comparison to similar studies with small datasets, which can be beneficial for medical specialists to make decisions and gain deeper knowledge about COVID-19 cases. The classification performance of the method can still be improved by increasing the number of training datasets. Also, the study still needs scientific testing but with higher performance, it can pave the way towards a modern and efficient diagnosis of the COVID-19. In the future, we aim to collect more radiology images of COVID-19 from local hospitals to make more superior results using the suggested model.

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