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COVID-19 Diagnosis Based on Multi Deep Neural Networks of Chest Lung X-Ray Images

Wessam M. Salama[1], M.B. Saleh[2], Moustafa H. Aly[3,*], Azza M. Elbagoury[1]

[1] Department of Basic Science, Faculty of Engineering, Pharos University, Alexandria, Egypt
[2] Department of Electronics and Communications Engineering, College of Engineering and Technology, Arab Academy for Science, Technology and Maritime Transport, Aswan, Egypt
[3] Department of Electronics and Communications Engineering, College of Engineering and Technology, Arab Academy for Science, Technology and Maritime Transport, Alexandria, Egypt

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ABSTRACT

In this paper, increased attempts are carried out to develop the deep neural networks to diagnose COVID-19 based on Chest X-Ray (CXR). This work introduces a new diagnostic system, utilizing different deep neural networks, InceptionV3, DenseNet121, ResNet50, VGG16 and MobileNetV2 models, to classify CXR images into healthy normal, pneumonia bacterial and COVID-19. Additionally, transfer learning and data augmentation techniques are utilized to solve the problem of scarcity of CXR images; hence the over-fitting of deep models will be avoided. The proposed end-to-end deep system is applied on the dataset sourced from COVID-19 lung CXR images from Kaggle and the IEEE8020 COVID-19 CXR dataset which is introduced by John Hopkins Hospital. The classification results reveal that diagnostic of CXR lung images by InceptionV3 provides the best results, with 98.87% accuracy, 98.88% area under the curve (AUC), 98.98% sensitivity, 98.79% precision, 97.99% F1- score and 1.4574 s computational time. Finally, the ensemble classifier with a voting strategy is proposed to boost the diagnosis performance using the multiple convolutional neural networks (CNNs) instead of one. The classification results are aggregated of each image using the voting technique. It is observed that the performance of the proposed ensemble classifiers with voting strategy reaches the state-of-art performance.

1. Introduction

Corona Virus 2019 (COVID-19) is a viral infection disease that has infected more than 1.3 million worldwide which caused more than 106,000 deaths and is still counting. Different studies [1-4] have reposted that the CXR scans reveal consistent radiological observations in COVID-19 patients. The scarcity of current COVID-19 samples prevents it from being processed by many powerful deep neural network models to reach a state-of-art classification performance without any human interface. Hence, several works [5-8] built deep learning models to automatically view CXR images and predict

* *Corresponding author.*
E-mail address: mosaly@aast.edu

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if CXR images are positive or negative for COVID-19. Because of privacy issues, the CXR images used in such works are not sharable to the public. So, their results cannot be reiterated and the learned models cannot be used in other hospitals. On the other hand, the lack of open access COVID-19 chest scans with its diagnostic results is greatly obstructed.

Deep learning [9] has achieved impressive results in the biomedical engineering field, especially the Deep Convolutional Neural Networks (CNN) which reach state-of-the-art performance. Data augmentation [10] is one of the strategies used to resolve the shortage of COVID-19 CXR images. It expands the training data collection as new samples that are created by performing random transitions to original images. Accelerating the convergence process and avoiding overfitting are the main advantages. Transfer learning technique [11] is utilized to retrain the model to reuse it instead of training from scratch. In [12], InceptionV3, DenseNet121, ResNet50, VGG16 and MobileNetV2 models were developed to describe deep learning for images classification process [13-15]. Since the detection of COVID-19 epidemic, intensified attempts are being made to develop deep learning approaches based on diagnostic screening images such as CXR scans to classify the cases as a positive or a negative COVID-19. Xiaowei Xu set an early-screening process focused on several CNN models to distinguish COVID-19 patient CT scans [16]. In comparison, CNN was used in [17] to classify CXR images of COVID-19 cases. Several researchers have used 3D deep models to diagnose COVID-19 by CXR examination [18- 20]. D.S. Kermany et al. proposed a transfer learning algorithm of initiation for the deep learning model to provide clinical diagnosis prior the pathogenic test [21]. G.V. Vijayalakshmi et al. introduced a Random Forest infection-size-aware (iSARF) approach that can automatically categorize subjects into classes of specific sets of infected lesion sizes [22]. For deep CNN, a vast number of training images is required to learn a model with millions of parameters. Also, the availability of image's ground truth plays an effectively role in applying CNN to medical field.

One of the major challenges to achieve proper classification using CXR images is the requirement for huge amounts of high-quality images, which are often unavailable in international databases. Similarly, there is criticism of the low number of positive pictures for assessing the robustness of the techniques or obtaining models with generalization potential for application in clinical settings. Because of the lack of pictures, the techniques utilized do not take the patients' condition into account, which is critical information that clinicians must address. As a result, the goal of this study is to enhance learning ability in the presence of a small collection of positive class samples.

Despite developments in deep learning algorithms for the detection and diagnosis of COVID-19, one of the most significant limitations of this modality in COVID-19 diagnosis is the lack of equipment in all medical and diagnostic facilities. Furthermore, many COVID-19 patients require multiple chest CT scans, where they are exposed to a lot of radiation during scans, which creates a lot of problems. Furthermore, there is a possibility of virus transmission from one patient to another due to tunnel contamination. As a result, CXR images are used in our framework to solve the CT image difficulties.

The main difference between our study and previous review studies evaluating automatic classification of COVID-19 using CXR images [20, 23-29, 31-33] is that none of them addressed the difficulties associated with lack of generalization, which have been identified in numerous articles.

In this paper, on CXR lung images, the Inception V3, DenseNet121, ResNet50, VGG16, and MobileNetV2 models are utilized to distinguish between healthy normal, bacterial pneumonia, and pneumonia induced by COVID-19. In addition, transfer learning and data augmentation are used to increase the quantity of CXR lung images in order to improve the performance of our proposed framework. Furthermore, this study introduces a new ensemble classifier that uses a voting mechanism to integrate the classification results of the five introduced deep CNNs to eliminate the incorrectly classified samples and improve accuracy.

Our methodology is divided into three phases which are summarized as the following:

-Utilizing the deep learning models, the Inception V3, DenseNet121, ResNet50, VGG16, and MobileNetV2, to classify our datasets into healthy normal, bacterial pneumonia, and pneumonia.
-The k-fold cross-validation technique is utilized to prevent the model from over-fitting.
-To overcome the lack of datasets and reduce computational time consuming, data augmentation and transfer learning techniques are applied to increase our models performance.
-Moreover, the ensemble classifier is introduced for voting mechanism to our classified results.

This paper is organized as follows. Section 2 shows the methodology used in our work, data augmentation, transfer learning and classification. The experimental results of the proposed classification systems are displayed in Section 3, followed by a comparison between the proposed diagnosis system and other recent methods using different datasets. Section 4 is devoted to the main conclusions.

2. Research Method

Our proposed technique is divided into three phases. First is the data augmentation and transfer learning. Second, image classification which is performed based on VGG16, ResNet50, InceptionV3, DenseNet121 and MobileNetV2 models. This work explores the classification of COVID-19 CXR images into healthy normal patients, pneumonia bacterial and pneumonia based on different deep CNNs. This relies on taking the advantage of the pre-trained VGG16, ResNet50, InceptionV3, DenseNet121 and MobileNetV2 models instead of training the CNNs from scratch. Training the deep model from scratch leads to overfitting, consuming time and the need of high computational resources. The k-fold cross-validation technique is utilized to prevent the model from over-fitting. This technique is especially used if the amount of data is limited and much of the available data, as possible, should be used for training. In the k-fold cross-validation, all the samples are divided randomly into groups, called k-fold values, of equal sizes. The (k-1) folds are used to learn the expected function, and the fold left out is used for testing. For example, in the five-fold cross validation, data is divided into five groups randomly. Every time, one group is chosen as a test set (20% from the total images) and the other four groups are used as training set (80% from the total images). For each k-fold, the data augmentation is added to the training sets, and the test set remains without any augmentation.

Finally, the voting ensemble technique is applied on the classification result of all five CNN models to build a robust ensemble classifier. Figure 1 explains our proposed classification framework.

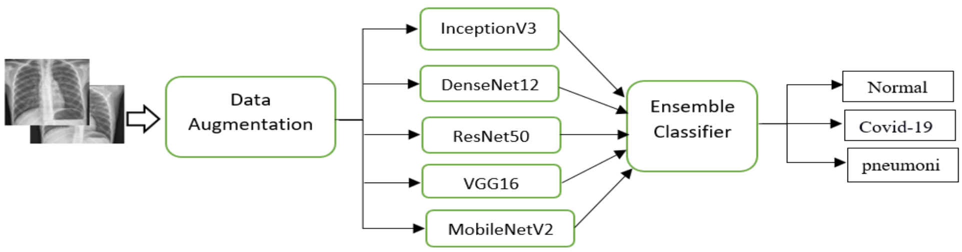

Fig.1. Block diagram of the proposed classification framework

2.1 Data Augmentation Phase

There are many strategies for data augmentation [10]. In this work, the rotation and shifting are performed. Each image rotates 180^{o} and width shift, height shift and zoom range is 0.2. As a result, each image is expanded to four images.

2.2 Transfer Learning

Transfer learning [11] is helpful when dealing with very limited datasets, e.g. COVID-19 CXR images that are more difficult to collect in greater numbers than other datasets. The pre-trained CNNs are utilized as an alternative to train the model from scratch. This approach is a golden key in speeding up and reducing the time of classification. We utilize the pre-trained InceptionV3, DenseNet121, ResNet50, VGG16 and MobileNetV2 models [13-15] in our framework.

2.3 Images Classification Phase Based on Deep Convolutional Neural Network

InceptionV3, DenseNet121, ResNet50, VGG16 and MobileNetV2 [7-10] are considered as the most success deep CNN models in classification. In this work, the aim is to take the full advantage of these pre-trained deep models, thus; the 1-channel greyscale CXR lung images will be concatenated along its third dimension. This concatenation is employed based on the deep CNN networks input which support three channels without any modification for hyper-parameters of the first networks' layers. In addition, instead of classifying 1000 classes, a new classification layer is added to categorize the three classes: normal, pneumonia bacterial, and pneumonia- COVID-19. Different models used in this work and their different parameters are discussed below.

2.3.1 InceptionV3 model

The iterations and the rate are set to 106 and 10-4, respectively. The number of the epoch is 60 and 1.4574 s computational time.

2.3.2 DenseNet121 model

The iterations and the rate are set to 105 and 10-2, respectively. The number of the epoch is 80 and computation time 1.9874s.

2.3.3 ResNet50 model

The iterations and the rate are set to 104 and 10-3, respectively. The number of the epoch is 130 and 2.5454s computational time.

2.3.4 VGG16 model

The iterations and the rate are adjusted to 105 and 10−4, respectively. The number of the epoch is 80 and 1.879s computational time.

2.3.5 MobileNetV2 model

The iterations and the rate are adjusted to 107 and 10-5, respectively. The number of the epoch is 160 and computational time 1.6547s.

2.4 The Ensemble Learning Method

The primary goal of this work is to diagnose COVID-19 with state-of-art accuracy; to help and provide the doctors and the researchers with trusted predictions. So, the ensemble classifier with voting strategy is proposed. The ensemble classifier boosts performance of classification using multiple models instead of one. The ensemble classifier helps improve the proposed classification technique performance by combining five CNN models' decisions into one classification model decision as shown in Figure 2; so, a higher accuracy is expected to be achieved.

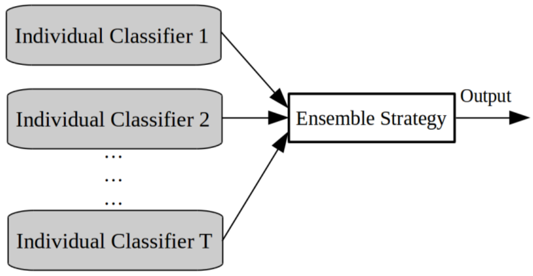

Fig.2. Block diagram of ensemble strategy

Averaging, voting and stacking are the three typical ensemble strategies [34]. Voting ensemble strategy is a method which performs better on classification tasks. For the same CXR image, the voting strategy lets the ensemble classifier generate the output result based on the majority classification result of the individual CNN. The nature of the proposed ensemble classifier allows each CNN to act as an error corrector for the others.

3. Results and Discussion

CXR lung scans play an important role in providing accurate, fast, and cheap screening tests of COVID-19. Kaggle Chest X-rays and the IEEE8020 COVID-19 Chest X-ray images by Dr. Cohen from John Hopkins Hospital are applied in this proposed work [35]. These images are combined to form one database consisting of three classes: Healthy Normal Patients, Pneumonia Bacterial and Pneumonia caused by COVID-19 virus traces. The proposed work target is to classify those three classes.

The used database comprises a CXR of total 306 images. To increase the total number of images, training images are augmented to four images using rotation range=180^{o}, width shift range, height shift range and finally, zoom range=0.2. The 5-fold cross-validation methodology is performed [36].

The accuracy, sensitivity, precision, F1- score, area under the ROC curve (AUC) and computational time are the evaluation metrics which will be used to assess the proposed model. Accuracy is a quantity to measure the correct predictions. Precision is the ratio of correctly predicted positive cases to the total actually positive cases. Sensitivity is the true positive rate or the ratio of correctly predicted positive cases to all cases. The F1-score combines precision and sensitivity, which is the harmonic mean of precision and sensitivity. So, it represents a more generalized metric from them. The AUC is the area under the curve of "Receiver Characteristic Operator" (ROC), which represents the performance of the model in classifying and distinguishing all classes. All these metrics are defined as follows [37].

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

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

$$Sensitivity = \frac{TP}{(TP+FN)} \quad (3)$$

$$F1 = 2\frac{(Pr \times Se)}{(Pr+Se)} \quad (4)$$

where TP is the true positive, TN is the true negative, FP is the false positive, and FN is the false negative. In order to authenticate the effect of data augmentation on the diagnosis results, the five deep CNN classifiers performance with and without data augmentation is explored are shown in Tables 1. These tables provide the ability for each CNN to correctly classify the CXR images into healthy normal patients, pneumonia bacterial and pneumonia caused by COVID-19. All the five CNNs are evaluated by the k-fold cross-validation technique. It is observed that the InceptionV3 classification performance without and with CXR lung images augmentation achieves the best attainment in terms of all performance metrics (accuracy, AUC, sensitivity, precision and F1-score).

Table 1
Average k-fold cross-validation classification with and without data augmentation for different models

Model	Accuracy %		AUC %		Sensitivity %		Precision %		F1-score %	
	Without	**With**	**Without**	**With**	**Without**	**With**	**Without**	**With**	**Without**	**With**
	Augmentation		**Augmentation**		**Augmentation**		**Augmentation**		**Augmentation**	
Inception V3	95.57% ±0.12	98.87% ±0.22	95.78% ±0.22	98.88% ±0.32	95.74% ±0.18	98.98% ±0.12	93.49% ±0.24	98.79% ±0.14	92.99% ±0.31	97.99% ±0.11
Dense Net121	93.89% ±0.32	96.99% ±0.42	94.54% ±0.22	97.14% ±0.32	94.67% ±0.24	97.47% ±0.12	94.15% ±0.13	97.49% ±0.33	94.54% ±0.18	97.24% ±0.22
ResNet50	92.99% ±0.42	96.87% ±0.52	93.47% ±0.22	96.47% ±0.12	93.51% ±0.12	97.01% ±0.32	93.24% ±0.14	97.11% ±0.28	93.59% ±0.13	96.99% ±0.12
VGG16	91.87% ±0.34	95.97% ±0.54	92.11% ±0.12	96.11% ±0.32	91.99% ±0.22	95.88% ±0.12	92.65% ±0.18	96.21% ±0.28	91.99% ±0.21	95.99% ±0.31
Mobile NetV2	88.88% ±0.42	93.88% ±0.12	89.14% ±0.22	93.97% ±0.32	88.89% ±0.18	93.78% ±0.28	89.27% ±0.19	93.87% ±0.29	88.99% ±0.12	92.99% ±0.32

Figures 3 and 4 explain the relation between true and false positive rates for CNNs with and without data augmentation, Inception V3, DenseNet121, ResNet50, VGG16 and MobileNetV2. True positive rates are defined as outcomes, where the model correctly predicts the positive class. In addition, the false positive rates are said to be the outcomes, where the model incorrectly predicts the positive class. It is observed from Figure 3 that the Inception V3 model with data augmentation achieves the best performance with AUC 98.88%, while MobileNetV2 achieves the worst results with AUC 93.97%. Moreover, Figure 4 introduces the true and false positive rates without data augmentation. It is shown from Figure 4 that the Inception V3 archives AUC 95.57% which is the best result and MobileNetV2 achieves AUC 93.88% which is the worst performance.

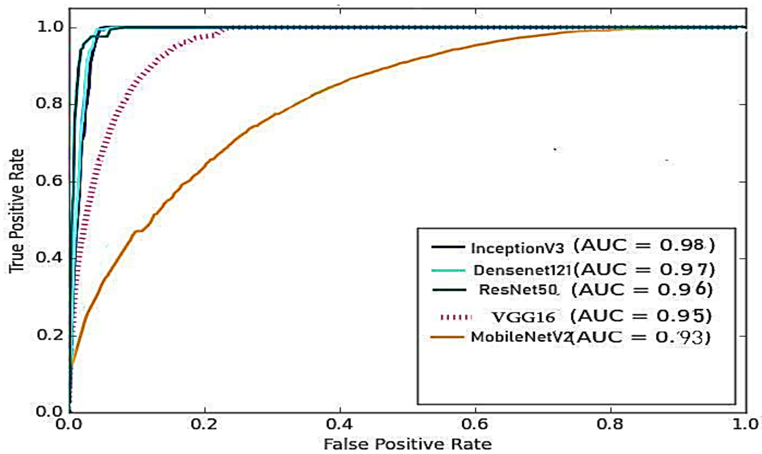

Fig. 3. Performance of introduced CNN models with data augmentation

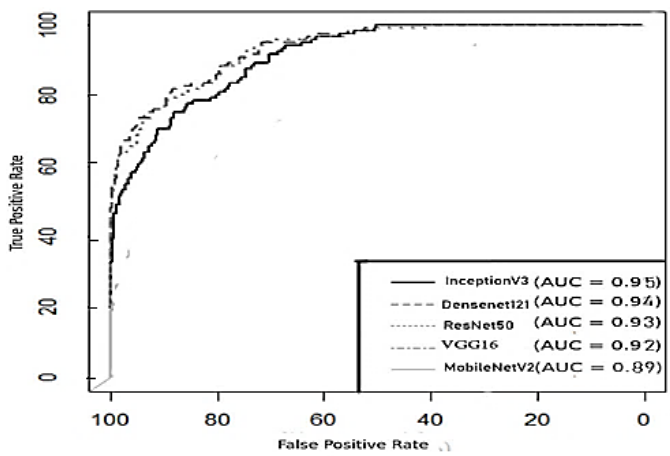

Fig. 4. Performance of introduced CNN models without data augmentation

To construct a robust classifier with state-of-art diagnosis performance, this paper proposed the ensemble classifier with a voting strategy which takes the prediction decision of each input image based on combining all the prediction results of the five CNNs classifiers. The diagnosis decision of the ensemble classifier will be considered according to the vast majority prediction by all the five CNNs for each CXR image.

Table 2 summarizes the performance assessment of the ensemble classifier. The performance metrics show the superiority for the diagnosis by the proposed ensemble classifier. The accuracy of 100% means that the voting from all classifiers is the same with the ground truth. Also, samples of the classified results of the five CNNs and the ensemble classifier are listed in Table 3. Each row consists of the image number, followed by the diagnosing of the six classifiers as normal, pneumonia bacterial and COVID-19 and finally the ground truth diagnosis. As shown, the proposed ensemble classifier puts together various outcomes from each CNN classifier network using a voting technique. The proposed ensemble classifier requires each CNN network to serve as an error corrector for the others. In addition, the ensemble classifier helps the model(s) that correctly forecasts the diagnosis to transcend the wrong decisions of the others.

Table 2
The proposed ensemble classifier with voting strategy

	Accuracy	Sensitivity	Precision	F1- score
Ensemble classifier	100%	100%	100%	100%

Table 3
Samples of CXR images classified by the five CNN classifiers and the proposed ensemble classifier

Image No.	Inception V3	DenseNet121	ResNet50	VGG16	MobileNetV2	Ensemble classifier	GT
1	Normal	Normal	Normal	Normal	Normal	Normal	Normal
2	Covid-19	pneumonia	pneumonia	pneumonia	Pneumonia	pneumonia	Pneumonia
50	Normal	Normal	pneumonia	pneumonia	Normal	Normal	Normal
55	Covid-19	Covid-19	Covid-19	Covid-19	Covid-19	Covid-19	Covid-19
56	Normal	Covid-19	pneumonia	pneumonia	Pneumonia	pneumonia	Pneumonia

The proposed frameworks for healthy normal patients, pneumonia bacterial and pneumonia caused by COVID-19 lung classification are compared with other recent works [38-40], and the results are shown in Table 4. It can be noted that the proposed system is superior over other systems. Our research is based on Keras, a high-level python that runs smoothly on Notebook GPU cloud (2 CPU cores and 13 GB RAM).

Table 4
Comparison between several classification methods based on different CNN architectures, datasets and our proposed models

Method	Data set	Accuracy	Sensitivity	Precision
Our proposed framework With ensemble classifier and voting strategy	**CXR images**	**100%**	**100%**	**100%**
DenseNet-169+ Transfer learning [38]	COVID-CT images	89%	89.3%	NA
ResNet50+ Support Vector Machine (SVM) [39]	CXR images	95.38%	NA	NA
Alex Net+ SVM [39]	CXR images	93.32%	93.41%	NA
DenseNet201+SVM [39]	CXR images	93.88%	94.35%	NA
DenseNet201+ Transfer learning [40]	SARS-CoV-2 Chest CT scan	97%	NA	NA
VGG-16 SDD [41]	X-ray	94.92%	94.92%	NA
DenseNet121-FPN [42]	CT images	NA	80.3%	NA
Xception and ResNet50V2 [43]	X-ray	95.5%		
VGG-16 [44]	X-ray	88.10%	97.62%	
ResNet-50 as backbone of main model [45]	CT images	NA	90%	NA
MobileNetV2 [46]	X-ray	96.78%	98.66%	NA
ResNet-50 [47]	X-ray	NA	95.33%	NA
BigBiGAN1 [48]	CT	NA	85%	NA

4. Conclusions

In this paper, different strategies, end-to-end, InceptionV3, DenseNet121, ResNet50, VGG16 and MobileNetV2 models, and ensemble classifier are applied to classify lung CXR images into healthy normal patients, pneumonia bacterial and pneumonia caused by COVID-19. Data augmentation and transfer learning are applied to overcome the lack of tagged COVID-19 dataset. AUC, Accuracy, Sensitivity, Precision, F1-score, and computational time are used to evaluate our framework. The experimental results assure that the InceptionV3 with data augmentation provides very accurate classification results over the introduced CNNs with an average AUC of 98.88%, accuracy of 98.87%, sensitivity of 98.98%, precision of 98.79% and F1-score of 97.99% for the used database, with computational memory requirements as low as possible. The results highlight the positive impact of using data augmentation and transfer learning in enhancing the classification performance. To take full advantage of the correct diagnostic classification result and discard the wrong diagnosis by each CNN classifier, this paper proposes the ensemble classifier with the voting strategy. The classification result indicates that combining the diagnostic results by each CNN by the voting strategy gives the state-of-art performance with an accuracy of 100%. The proposed methodology can assist in COVID-19 pandemic with a trusted diagnostic decision. Therefore, the proposed classifier depends on the powerful attainment of the deep models. The proposed technique is explored by comparing it with COVID-19 classification systems in the literature, and the results obtained demonstrate the superior success of the proposed method.

In the future, a pre-processing or post pre-processing could be applied to the CXR images. Moreover, segmentation algorithms based on U-Net or SegNet are performed to extract the region of interest (ROI) to increase the framework performance.

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