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Research paper

Improving the Diagnosis of COVID-19 using a Combination of Deep Learning Models

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Abstract

Background and Objectives: COVID-19 disease still has a devastating effect on society health. The use of X-ray images is one of the most important methods of diagnosing the disease. One of the challenges specialists are faced is no diagnosing in time. Using Deep learning can reduce the diagnostic error of COVID-19 and help specialists in this field.

Methods: The aim of this model is to provide a method based on a combination of deep learning(s) in parallel so that it can lead to more accurate results in COVID-19 disease by gathering opinions. In this research, 4 pre-trained (fine-tuned) deep model have been used. The dataset of this study is X-ray images from Github containing 1125 samples in 3 classes include normal, COVID-19 and pneumonia contaminated.

Results: In all networks, 70% of the samples were used for training and 30% for testing. To ensure accuracy, the K-fold method was used in the training process. After modeling and comparing the generated models and recording the results, the accuracy of diagnosis of COVID-19 disease showed 84.3% and 87.2% when learners were not combined and experts were combined respectively.

Conclusion: The use of machine learning techniques can lead to the early diagnosis of COVID-19 and help physicians to accelerate the healing process. This study shows that a combination of deep experts leads to improve diagnosis accuracy.

Introduction

COVID-19 is a family of SARS viruses that was first observed in January 2020 in Wuhan, China [1]. Most coronaviruses are originated from animals and can be transmitted to humans due to their zoonotic nature. Among these viruses, SASR-COV and MERS-COV can cause death in humans [2]. COVID-19's mutated structure makes it difficult to find an effective solution to the disease, and this has led to the death of many people in various countries, including the United States, China, Italy, Iran, etc. [2], [3]. Unlike SARS, COVID-19 affects internal organs such as the liver and kidneys in addition to the respiratory system.

The virus can eventually lead to death by weakening the immune system [5]. Recently, the use of artificial intelligence methods with a deep learning approach in various areas of machine learning such as image recognition, image classification and segmentation has been considered by researchers [6], [7].

Attention to deep learning in the diagnosis of various diseases has led to valuable results [8], including diagnosis of coronary heart disease using deep learning [9], diagnosis of tumor and its volume in the lungs and Breast [12] diagnosis brain tumor [11] and classification of diabetic retinopathy [10].

The use of deep learning in the diagnosis of diseases from x-ray images has also been considered, for example, a study conducted to diagnose pneumonia using this type of image [13]. Although accurate CT images are reliable and can detect lung infections, pneumonia and tumors and produce clearer images of tissues and organs, but using x-rays images is faster, easier, more accessible, cheaper and less harmful. Therefore, the diagnosis of COVID-19 from these images can help speed up the timely treatment of this disease [14], [15]. There are three general methods for applying deep learning from x-ray images: 1- using fine-tuned models, 2- using unfine-tuned models and 3- pre-trained models [16]. For example, in the one study by using Resnet Deep Learner, labels such as age and gender were used to classify the dataset, and finally, a classification was performed using an MLP classifier [17]. In another study, pneumonia was diagnosed using VGG-16 and inceptionV3 models. In this study, the dataset was divided into three classes: Partial Pneumonia, Viral Pneumonia and Normal Pneumonia, and the classifier SVM was used [18]. The use of deep convolutional learner with innovative architecture and using CT images has been done in some studies to diagnose COVID-19 [19]. Also, the use of two-dimensional and three-dimensional images and its detection by deep learners has been considered. [20]. In an another study a network called COVID-net [21], which expands and compresses layers in deep learning, it was claimed that it could increase the accuracy of diagnosing COVID-19 [22]. In another research, pre-trained networks such as inceptionv3, ResNet50, Resnet72 using the transfer method (Transfer Learning Method) were used to diagnose COVID disease from X-ray images [23]. Transfer learning is the reuse of a pre-trained model on a problem. It's currently very popular in deep learning because it can train deep neural networks with comparatively little data. This is very useful in the data science field since most real-world problems typically do not have millions of labeled data points to train such complex models. One of the most important challenges we face in diagnosing COVID 19 disease is how to increase the accuracy of learners [24].

In this study, an attempt has been made to increase the accuracy of detection of COVID-19 from X-ray images of The model presented here uses a combination of AlexNet, GoogleNet, SqueezeNet, and MobileNetv2 networks to provide a framework called deep experts combination. By summarizing the opinions of the above networks, the model can increase the accuracy of diagnosing COVID-19 disease. It may summarize the opinions of the above networks, and enhance the accuracy in the diagnosis of COVID-19.

Databases, Models, Proposed Method

A. Dataset

The dataset used in this study was obtained from the GitHub open-source repository shared by Dr. Joseph Cohen et al [25]. In this dataset, we only considered the x-ray images, and in total, there were 127 X-Ray images diagnosed with COVID-19, 500 X-ray images of healthy humans, and 500 cases identified as pneumonia. We studied 43 and 84 images of x-ray due to COVID-19 infected males and females respectively. They had an average age of 55 years. Fig. 1 shows examples of people with COVID-19 identified by professionals. In all deep models, 70% of the data is used for training and 30% for testing. K-fold cross-validation technique was also used to increase accuracy.

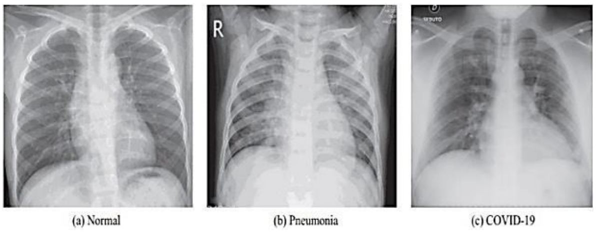


Fig. 1: An example of a normal image, pneumonia and COVID19.

B. MobileNet Deep Network (MobileNetv2)

MobileNet-v2 Network is used to image detection and segmentation. It can provide higher recognition accuracy than MobileNet while no more parameters and computation costs are needed. MobileNetv2 is very similar to the original MobileNet (MobileNetv1). In the other hand, MobileNetV1 has 13 depth-wise separable convolution whereas MobileNetV2 has got 17 of them. MobileNetV2 uses depth-wise separable convolution as efficient building blocks.

Table 1: Structure and parameters of MobileNet network

Type	Stride	Filter Size	Output Size
Convolution	2 ×2	3×3×3×32	224×224×۳
Convolution DW	1×1	3×3×32	112×112×32
Convolution	1×1	1×1×32×64	112×112×32
Convolution DW	2 ×2	3×3×64	112×112×64
Convolution	1×1	1×1×64×128	56×56×64
Convolution DW	1×1	3×3×128	56×56×128
Convolution	1×1	1×1×64×128	56×56×128
Convolution DW	2 ×2	3×3×128	56×56×128
Convolution	1×1	1×1×128×258	28×28×128
Convolution DW	1×1	3×3×256	28×28×256
Convolution	1×1	1×1×256×256	28×28×256
Convolution DW	2 ×2	3×3×256	28×28×256
Convolution	1×1	1×1×256×512	14×14×256
Convolution DW	1×1	3×3×512	14×14×512
Convolution	1×1	1×1×512×512	14×14×512

However, linear bottlenecks between the layers and shortcut connections between the bottlenecks are two new features of MobileNetV2. The basic structure is shown in Table 1.

The network has an image input size of 224×224×3. It is divided into two separate layers, which are depth wise convolution and pointwise convolution. Depth wise layer is responsible for filtering while pointwise layer for combining feature maps coming from different channels. By this splitting operation, the computation cost is greatly decreased [26]. After the depth-wise separable convolution, the ReLU operation on the low-dimensional features is easy to cause information loss [27].

C. Squeezenet Model

Now let us to describe the SqueezeNet architecture. SqueezeNet is a smaller CNN architecture that uses fewer parameters while obtaining accurate [28]. Table 2 shows that SqueezeNet begins with a convolution layer, followed by 8 Fire modules, ending with a final conv layer. The number of filters per fire module gradually is increased from the beginning to the end of the network. SqueezeNet performs max-pooling with a stride of 2 after layers first conv, fire4, fire8, and final conv. Fire modules architecture consist of two layers, squeeze layer and expand layer, both of them are the main key to SqueezeNet architecture. Squeeze layer is a layer composed of three convolution layers with each size 1×1. Expand layer is a layer composed of a combination of four lxl convolution layers and four 3x3 convolution layers. The full architecture is presented in Table 1.

Table 2: SqueezeNet architecture

Type	Stride	Filter Size	Output Size
Input	-	-	224×224×3
Convolution	2	96×96×7	109×109×96
Pooling	2	3×3	54×54×96
Fire 2	-	16×16×1, 64×1×1, 64×3×3	54×54×128
Fire 3	-	16×16×1, 64×1×1, 64×3×3	54×54×128
Fire 4	-	3×3×1, 128×1×1, 128×1×32	54×54×256
Pooling	2	3×3	27×27×256
Fire 5	-	32×1×1, 128×1×1, 128×3×3	27×27×256
Fire 6	-	48×1×1, 192×1×1, 192×3×3	27×27×384
Fire 7	-	48×1×1, 192×1×1, 192×3×3	27×27×384
Fire 8	-	64×1×1, 256×1×1, 256×3×3	27×27×512
Pooling	2	3×3	13×13×128
Fire 9	-	64×1×1, 256×1×1, 256×3×3	13×13×512
Convolution	1	6×13×13	13×13×6
Pooling	-	13×13	1×1×6

D. Alexnet Network Model [29]

AlexNet has eight layers; the first five were convolutional layers. It can be seen from Table 3 that the back of the first, second and fifth convolutional layers is the pooling layer. The calculation process of the convolutional layer is as follows and the last three were fully connected layers. It has been proven that the network has learned rich feature representations for a wide range of images. The network has an image input size of 227-by-227(is 224 × 224 × 3). Table 3 shows the parameters used in this study in the Alex network.

Table 3: Structure and parameters of AlexNet network

layer	Stride	Filter Size	Kernel
Convolution	4	55×55×96	11×11
Max Pooling	2	27×27×96	3×3
Convolution	1	27×27×256	5×5
Max Pooling	2	13×13×256	3×3
Convolution	1	13×13×384	3×3
Convolution	1	13×13×384	3×3
Convolution	1	13×13×256	3×3
Max Pooling	2	6×6×256	3×3
FC	-	9216	-
FC	-	4096	-
FC	-	4096	-
FC	-	1000	-

E. Google Net network model (GoogleNet) [30]

GoogleNet is a type of convolutional neural network based on the Inception architecture. Table 4 shows that, Convolution and max-pooling operations are performed on the input, respectively. Then sent into the next inception module. Fig. 2 shows a part of the Google Net model called Inception-v3, introduced in 2015 by Szegedy et al [31]. In this model, Kernels with dimensions of 1 × 1, 3 × 3 and 5 × 5 are applied to the input. The outputs of all these layers are merged together to be considered as the input of the next layer.

Table 4: The general structure and parameters of the Google Net network

layer	Stride	Filter Size
Convolution1	4	3×224×224
Max Pooling1	2	64×112×112
Convolution2	1	64×56×56
Max Pooling2	2	192×56×56
Inception3a	1	192×28×28
Inception3b	1	256×28×28
Max Pooling3	1	480×28×28
Inception4a	2	480×14×14
Inception4b	-	512×14×14
Inception4c	-	512×14×14
Inception4d	-	512×14×14
Inception4e	-	528×14×14
Max Pooling4		832×14×14
Inception5a		832×7×7
Inception5b		832×7×7
Max Pooling5		1024×7×7
FC		1024×1×1

F. The Classification Method

In a learning system, there must be a balance between the accuracy and the generalization ability. Feature selection and data validation in this learning system is done for the classification [32].

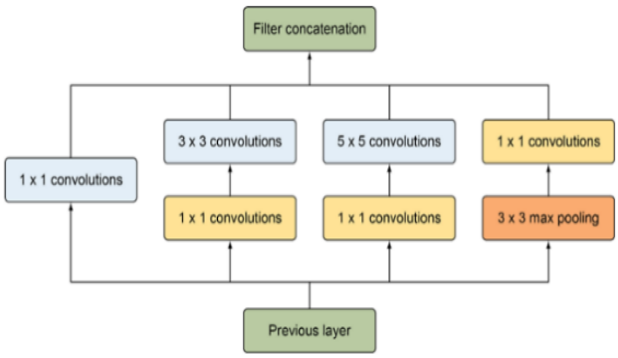


Fig. 2: Inception model.

Proposed Method

A crucial issue in CNN is to determine how much training data is needed to achieve a good level of the accuracy, especially in the field of medicine which is subjected to the lack of standardized data. For example, to train AlexNet, we need about 60 million images. In addition, training a Convolutional Neural Network (CNN) requires powerful hardware. To solve this problem, researchers use two methods: 1- fine-tuned networks 2- apply CNN to extract features and then send them to classifiers [32].

In the first method, the CNN network may not be able to train and predict the parameter because the numbers of the image are not enough. In this case, the network parameters can be reset. In the second method, (when we use a large amount of training data for the network) the number of images are enough and CNN can extract features from images and classifying them by a classifier such as SVM or MLP.

In this study, in order to diagnose COVID-19, the first method has been used which called transfer is learning. In deep learning, transfer learning is a technique whereby a neural network model is first trained on a problem similar to the problem that is being solved.

There are many models which have been trained with large amount of training data. For example, Transform Learning (TL) is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task. Therefore, it allows rapid progress and improved performance.

The process of TL consists of two stages: 1) Choose a pre-trained Deep Learning model .2) rearranging the designed model based on the size of the dataset and its features. Fig. 3 shows how to use the TL technique in this study.

Nowadays, CNN models are widely used. This is because of its strong ability of high-speed parallel processing. In this study, we present combing the ideas of deep models to increase the accuracy of COVID-19 detection because the total experimental results of classifiers indicate increase in overall classification accuracy.

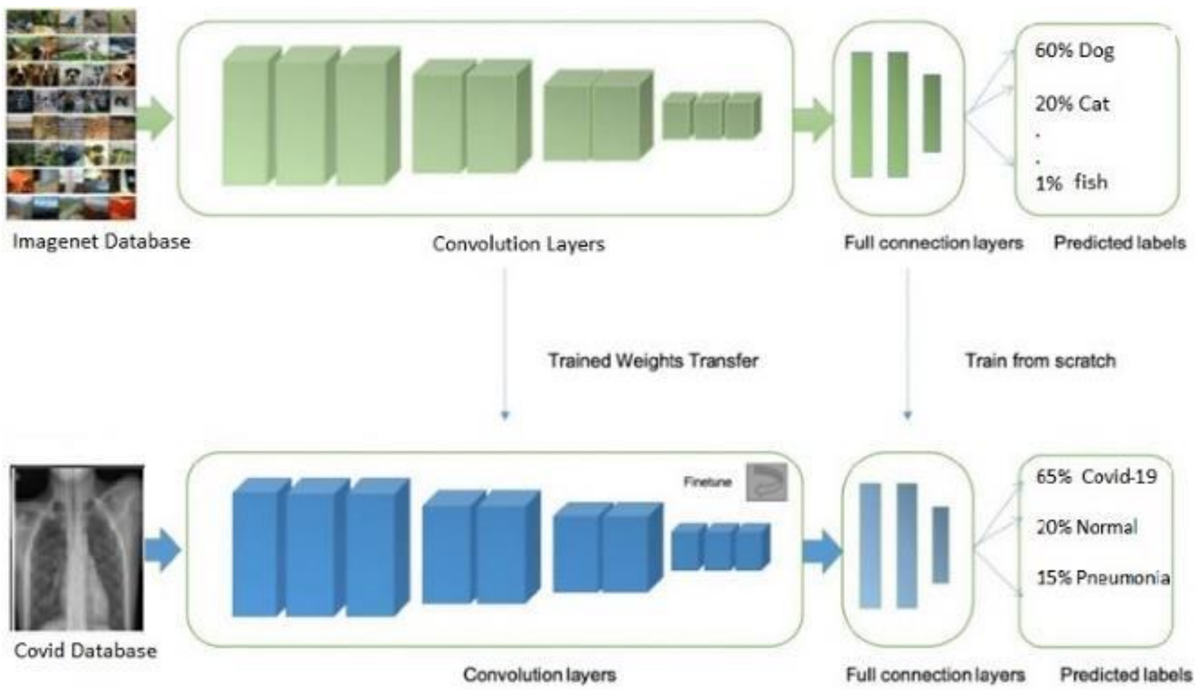


Fig. 3: Using the transfer learning technique to transfer weights to deep nets to diagnose COVID-19.

The proposed method used a combination of deep models for classification. This mechanism, called the combination of experts, divides the input space into subsets and then assigns each subset to a classifier [34]. These subsets are divided based on the target. The feature vector for the input was represented by the fully connected (FC) layer where each input is connected to all neurons. If present, FC layers are usually found towards the end of CNN architectures and can be used to optimize objectives [35]. The output is a vector with N components. N is the number of classes that classifiers predict them. In this study there are 3 classes include normal, Pneumonia and COVID-19. The purpose of CNN is to generate an output vector with N components. Each number shows the probability of belonging to the desired class. Probability can also be written as a percentage ,and the highest percentage indicates the final result.

The ultimate goal of the deep model is to reduce the error between predicted values and expected values which is referred to as the Cost Function. Generally, there are various methods for estimation of a cost function such as Gradient Descent, batch Gradient Descent, Stochastic Gradient Descent etc. In this study, a Stochastic descending gradient algorithm has been used to optimize the cost function in the diagnosis of COVID-19. Training a CNN classifier on small datasets does not work well. In contrast to this problem, various techniques are used such as the production of Synthetic Data or data augmentation. In this study, rotating, zooming and moving X-ray images have been used to augment data. In the proposed method, 4 deep models were used and after using the weight transfer technique in all deep models, the probability percentage was collected from the fully connected layer of each network. Finally, probability percentage was sent to a module called Majority Voting. A multilayer perceptron (MLP) is a class of feedforward artificial neural network (ANN) used in this model for classification method. The term MLP is used ambiguously, sometimes loosely to mean any feedforward ANN, sometimes strictly to refer to networks composed of multiple layers of perceptrons (with threshold activation. Fig. 4 shows the proposed method. It should be mentioned that the Support Vector Machine (SVM), Decision Tree, or any other classification method can be used as an alternative. For example, if the probability of sample x belonging to class j in GoogleNet, Alex Net, MobileNetv2 and in Squeeze Net is p1, p2, p3 and p4 respectively, the majority vote of the experts is calculated based on (1):

$$p_{xe}^{j} = \frac{\sum_{i=1}^{n}(px_i^j)}{n} \qquad (1)$$

where px_i^j is the probability of sample x belongs to class j from point of view expert i, n number of experts (in this study n = 4). p_{xe}^{j} is the total expert opinion on the probability of sample x belongs to class j. It should be mentioned that p_{xe}^{j} maybe greater than 100. In order to solve this problem, (2) is used:

$$p_{xne}^{j} = \frac{100 \times p_{xe}^{j}}{\sum_{j=1}^{c}(p_{xe}^{j})} \qquad (2)$$

where p_{xe}^{j} is a total expert opinion about p_{xne}^{j} is the normalized probability. For example, in sample x if GoogleNet, AlexNet, MobileNetv2 and Squeeze Net with probabilities of 40%, 40%, 50% and 40% respectively, belonging to the normal class and with probabilities of 30%, 20%, 30% and 40% belonging to the pneumonia class and with a probability of 30%, 40%, 20% and 20% belonging to the COVID-19 class, total expert opinion to the normal class, the pneumonia class and the COVID-19 class is 42.5%, 30% and 27.5% respectively. Therefore, this sample belonging to the normal class. The training parameters used in the four networks are shown in Table 5.

Table 5: Parameters used in the training phase in deep networks

Learning Parameters	Google Net	Alex Net	Squeeze Net	Mobile Netv2
Learning rate	3e-4	3e-4	3e-4	3E-4
Batch size	10	10	10	10
Optimizer	NG*	NG*	SGD**	SGD**
Loss Function	C	C	C	C
Epochs per each Training Phase	100	100	100	100
Horizontal/Vertical flipping	yes	Yes	Yes	YES
Zoom Range	5٪	5٪	5٪	5٪
Rotation Range	٠	٠	٠	٠
Width/Height shifting	5٪	5٪	5٪	5٪
Shift Range	5٪	5٪	5٪	5٪
Re-scaling	1/25	1/25	1/25	1/25

SGD: Stochastic Gradian Descend NG: Nadam Categorical C: Crossentopy

Results and Discussion

The software MATLAB 2019 was used to train a deep model and a computer with Microsoft Windows 10 64-bit version was used for the experiment. Its specifications were as follows: Intel 3687 @ i7 processor, 8G of RAM, and 1G of graphics memory.

To assess the reliability of the proposed method we considered the following standard metrics: Accuracy, Sensitivity, Specificity and F1_score. These metrics are calculated on the concept of the true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) scores:

-TP is the amount of positive COVID-19 that were correctly labelled as positive.

- FP is the amount of negative (healthy) COVID-19 that was mislabeled as positive.

- TN is the amount of negative (healthy) COVID-19 that was correctly labelled as healthy.

- FN is the amount of positive COVID-19 that were mislabeled as negative (healthy).

Accuracy: Accuracy is one metric for evaluating classification models .it is computed as (3):

$$Accuracy = \frac{\sum True\ positive + True\ negative}{\sum Total\ population} \tag{3}$$

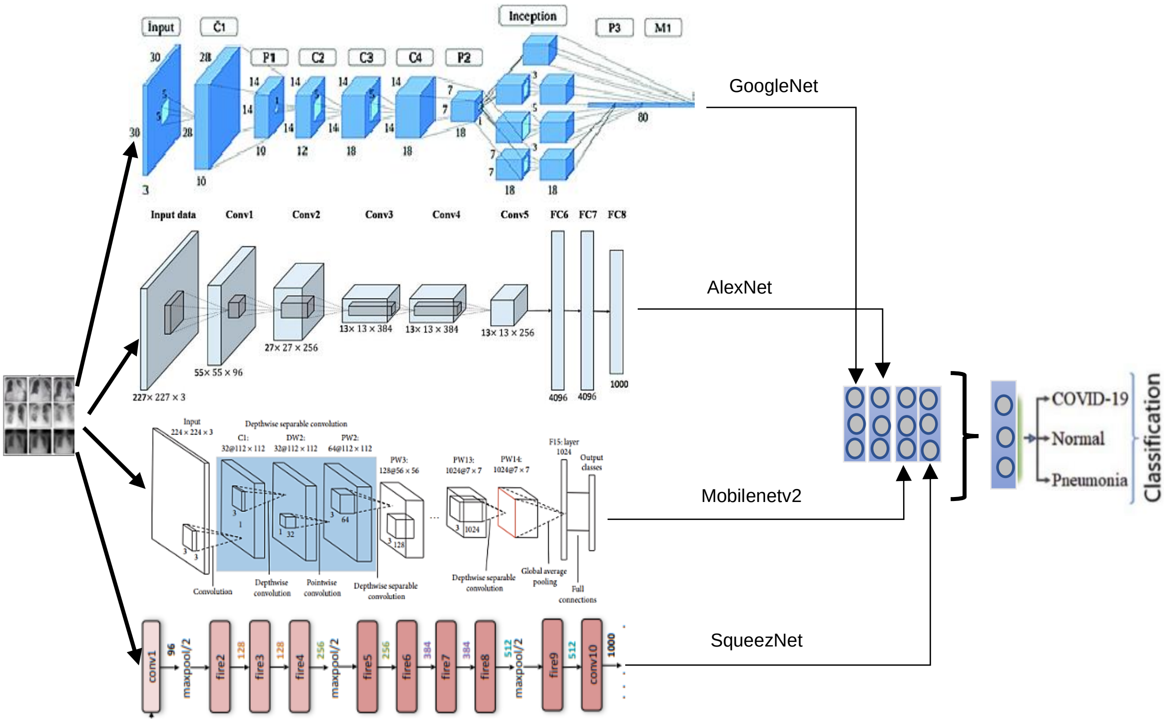


Fig. 4: Proposed method.

Sensitivity and specificity are metrics of the performance of classification test that is widely used in (4) and (5):

$$(Sensivity) = \frac{TP}{TP + FN} \tag{4}$$

$$(\mathrm{Specificity}) = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \tag{5}$$

The F1-score is a measure of a test's accuracy. It is calculated as (6):

$$(F1_{score}) = \frac{Sensivity \times Precision}{Sensivity + Precision} \times 2 \tag{6}$$

The obtained results according to the metrics mentioned are shows in Table 7 and Table 8. As mentioned, in order to evaluate the model k-fold cross-validation technique with k=5 has been used. At the end of 5-fold, the average accuracy was calculated. Fig. 5 shows how to use the k-fold method for five-class. The results obtained in some folds in the deep models of Google Net, AlexNet, MobileNet and SqueezeNet are shown in Fig. 6.

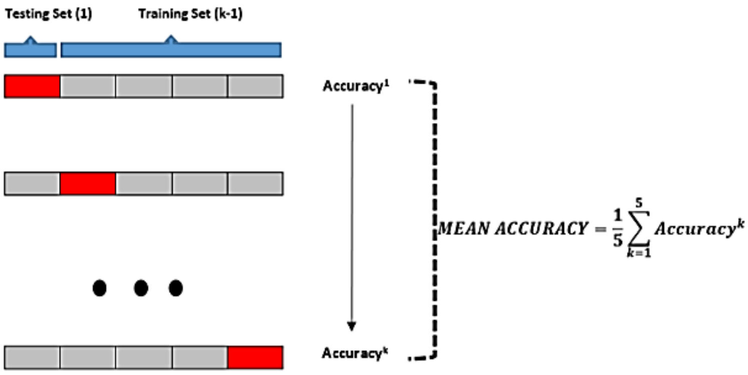


Fig. 5: k-fold cross-validation (k = 5).

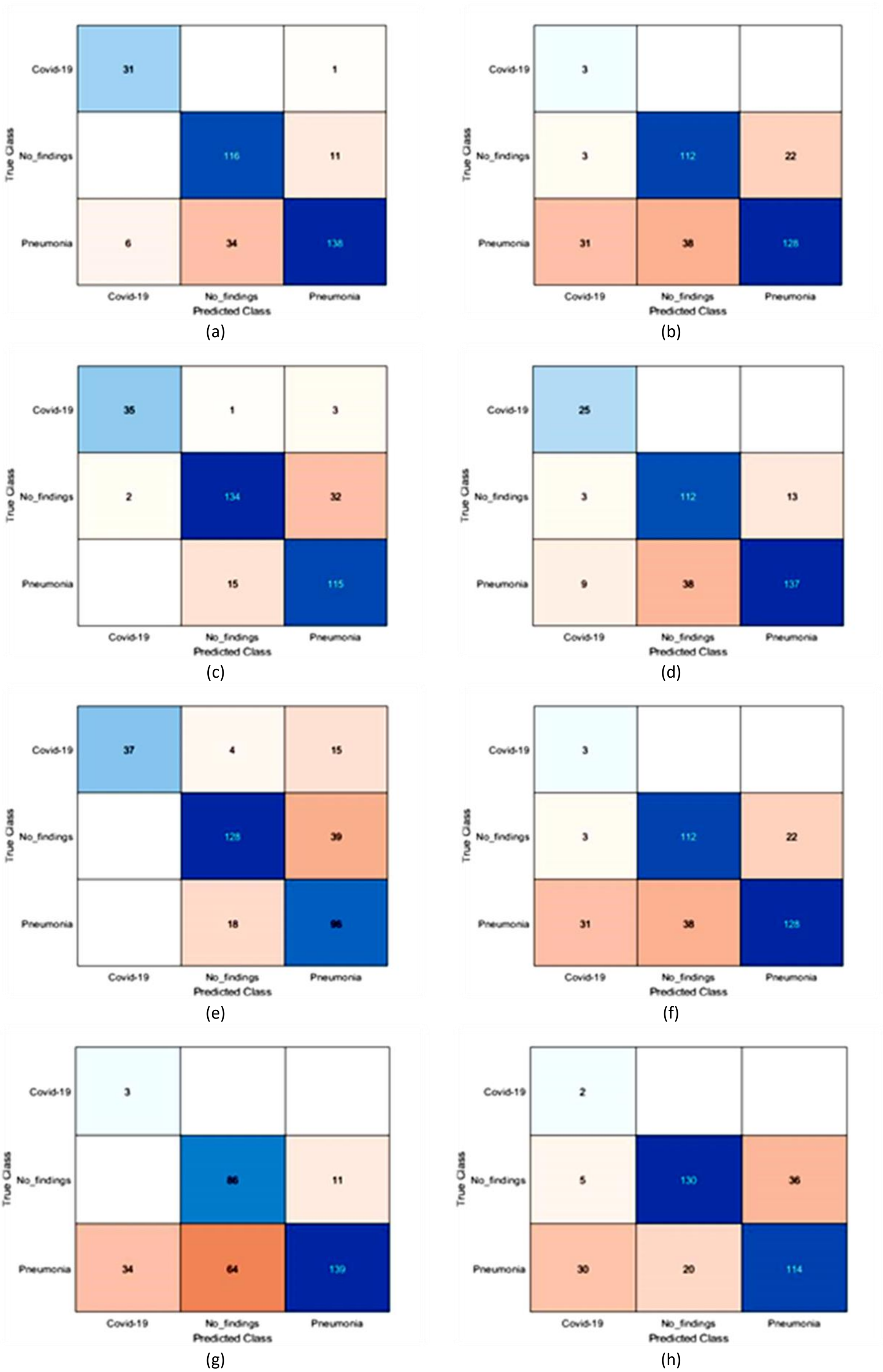
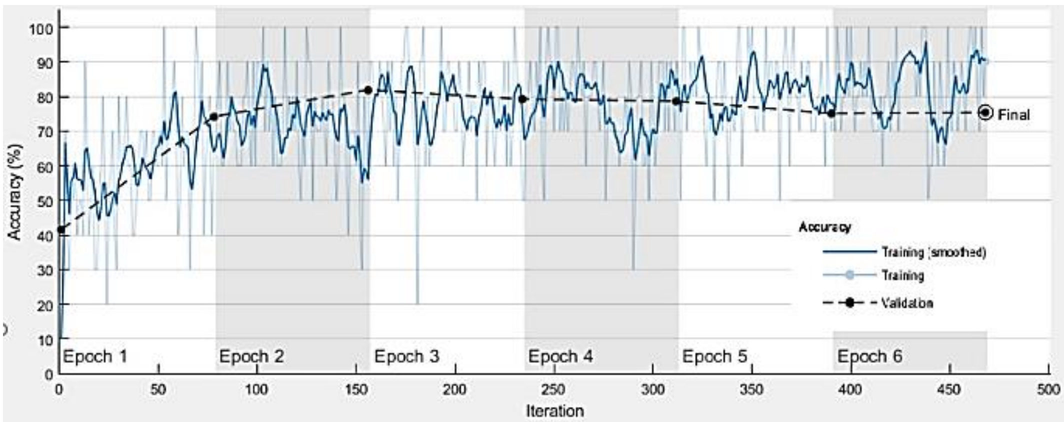


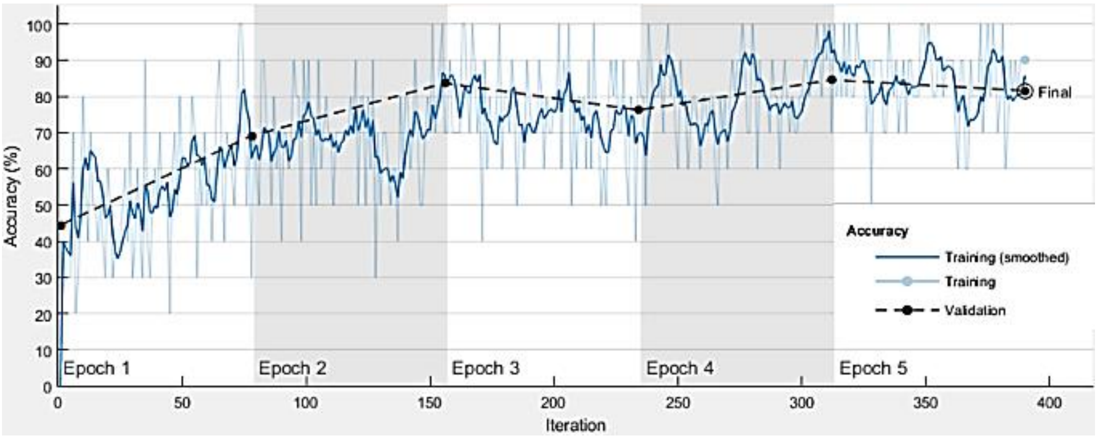
Fig. 6: The confusion matrix of the network for fold 1 and 3. (a): GoogleNet fold 3, (b): GoogleNet fold 1, (c) AlexNet fold 3, (d): AlexNet fold 1, (e): MobileNet fold 3, (f): MobileNet fold 1, (g): SqueezeNet fold 3, (h): SqueezeNet fold 1.

Table 6: Results of different folds in each deep models of Google Net, AlexNet, MobileNet and Skiesnet

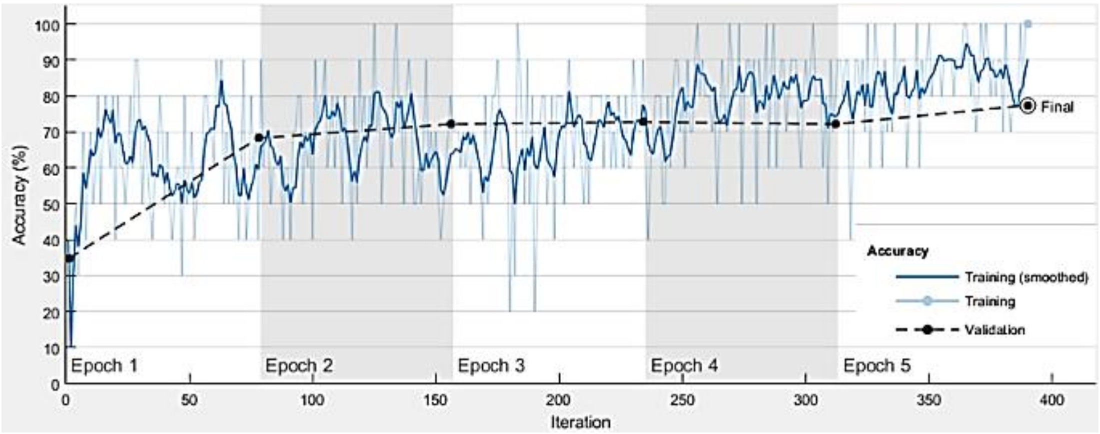
	Fold	COVID19 Correct detected	COVID19 Not detected	COVID19 Wrong detected	Pneumonia Correct detected	Pneumonia Not detected	Pneumonia Wrong detected	Normal Correct detected	Normal Not Detected	Normal Wrong detected	Acracy
MobileNet	1	33	3	4	112	25	28	129	28	21	٪84/3
MobileNet	2	36	7	1	111	11	39	129	33	11	٪84/9
MobileNet	3	32	1	5	127	27	23	127	23	23	٪84/9
MobileNet	4	35	3	2	113	14	37	137	35	13	٪84/6
MobileNet	5	36	6	1	106	14	44	136	39	14	٪82/5
GoogleNet	1	34	0	3	136	27	14	136	14	24	٪76
GoogleNet	2	31	1	6	138	40	12	138	34	11	٪75/1
GoogleNet	3	35	4	2	115	15	35	134	34	16	٪74/3
GoogleNet	4	34	3	3	130	16	20	129	31	21	٪76/9
GoogleNet	5	35	2	2	133	14	27	125	23	25	٪76/9
Alex Net	1	35	6	2	117	14	33	135	30	25	٪85/2
Alex Net	2	35	4	2	115	15	35	134	34	16	٪84/3
Alex Net	3	25	0	12	137	47	13	112	38	16	٪84/2
Alex Net	4	35	2	4	100	16	50	132	34	18	٪81/1
Alex Net	5	34	3	3	115	10	35	133	30	17	٪83/9
Squeeze Net	1	2	0	35	114	50	36	130	41	20	٪73
Squeeze Net	2	3	0	34	139	11	98	86	64	11	٪67/7
Squeeze Net	3	3	0	34	128	69	22	112	25	38	٪72/1
Squeeze Net	4	4	1	33	130	45	30	117	20	33	٪74/4
Squeeze Net	5	3	1	34	132	41	28	115	23	35	٪75



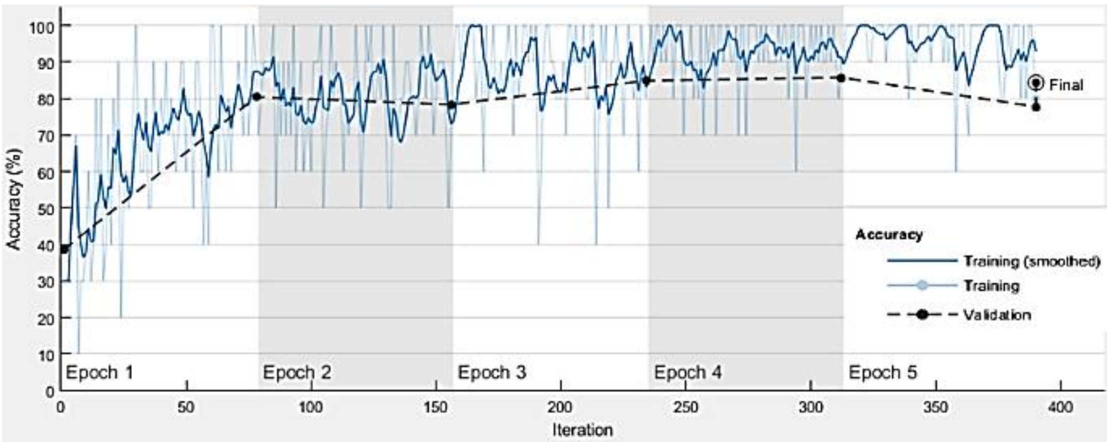
(a)



(b)



(c)



(d)

Fig. 7: Training and testing processes in the 4 network. (a): AlexNet, (b): GoogleNet, (c): SqueezsNet, (d): MobileNet.

Table 7: The number of true and false positives and false negatives for each network

	COVID19 Correct Detected	COVID19 Not Detected	COVID19 Wrong Detected	Pneumonia Correct Detected	Pneumonia Not Detected	Pneumonia Wrong Detected	Normal Correct Detected	Normal Not Detected	Normal Wrong Detected
GoogleNet	22	2	15	142	8	75	90	60	7
AlexNet	30	3	7	18	41	136	136	41	14
MobileNet	35	2	8	22	30	121	121	29	15
SqueezeNet	37	·	19	54	18	128	128	22	39
Mixture of Experts	36	1	3	18	25	126	126	24	15

Table 8: Evaluation metrics

		Sensitivity	**Specificity**	**F1-Score**	**Final Accuracy**
GoogleNet	Covid19	0.59	0.99	0.72	**75.4%**
	Normal	0.60	0.96	0.72	
	Pneumonia	0.94	0.60	0.77	
AlexNet	Covid19	0.54	1	0.70	**81.6%**
	Normal	0.91	0.77	0.83	
	Pneumonia	0.84	0.85	0.77	
MobileNetv2	Covid19	0.94	0.97	0.87	**84.3%**
	Normal	0.80	0.91	0.85	
	Pneumonia	0.85	0.83	0.83	
SqueezeNet	Covid19	1	0.93	0.79	**77.4%**
	Normal	0.85	0.79	0.80	
	Pneumonia	0.64	0.90	0.72	
Mixture of Experst	Covid19	0.89	0.99	0.92	**87.2%**
	Normal	0.80	0.93	0.86	
	Pneumonia	0.91	0.81	0.85	

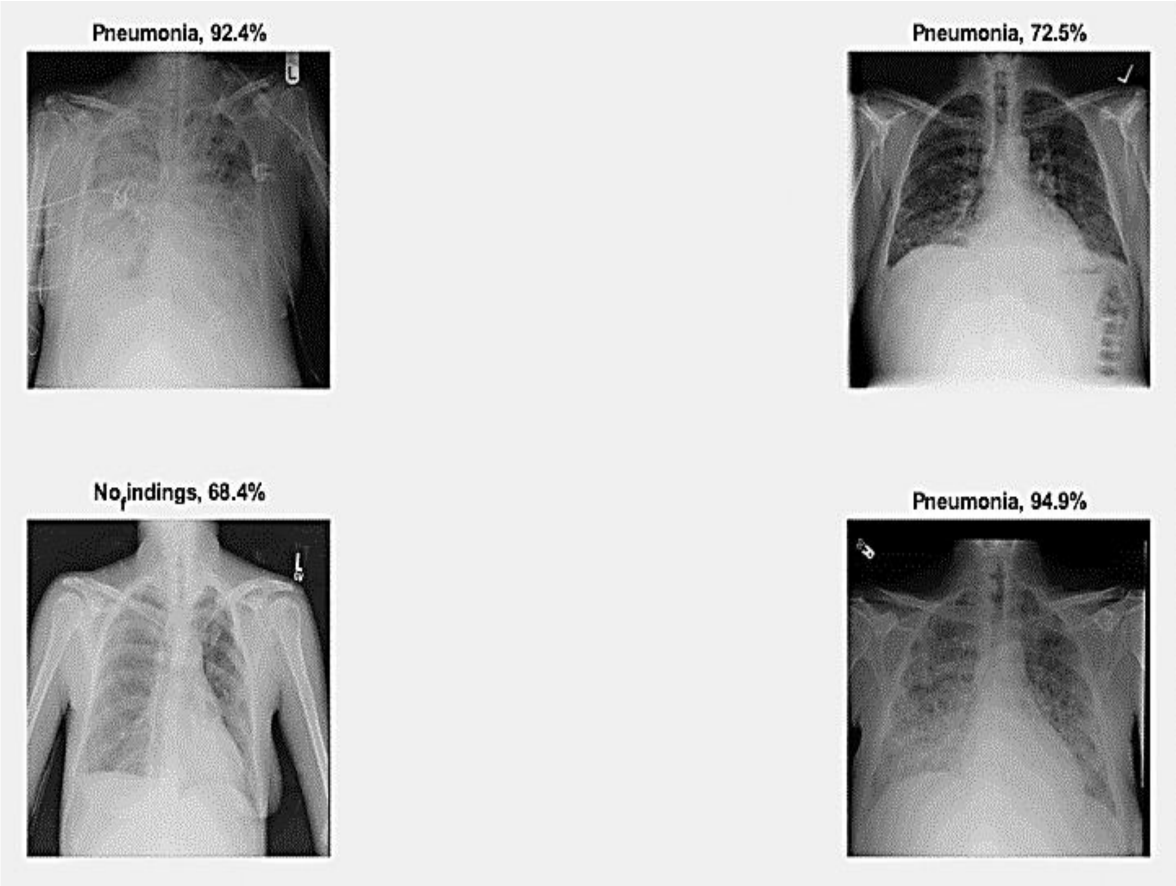


Fig. 8: The sample of Mixture of experts.

Conclusion

Classification with Deep Convolutional Neural Networks proposed by Alex Krizhevsky et al. built a new landscape in Computer Vision by destroying old ideas in one masterful stroke.

The paper used a CNN to get a Top-5 error rate (rate of not finding the true label of a given image among its top 5 predictions) of 15.3%. The next best result trailed far behind (26.2%).

This architecture is popularly called AlexNet. Number of parameters for alexnet is 60M parameters. One focus of GoogLeNet was to address the question of which sized convolution kernels are best. Previous popular networks employed choices as small as 1×1 and as large as 11×11. One insight in GoogLeNet was that sometimes it can be advantageous to employ a combination of variously-sized kernels.

The parameter for google net is 4 M parameters. MobileNetV2 is very similar to the original MobileNet, except that it uses inverted residual blocks with bottlenecking features. It has a drastically lower parameter count than the original MobileNet.

MobileNets support any input size greater than 32 x 32, with larger image sizes offering better performance.

Since the classification algorithms are not suited for all problems alone, combining expert's opinions can be a solution [36].

An idea in this research is the combination of deep learning networks in parallel. This method is also called majority vote or collective wisdom.

The results show that the combination of deep learning networks and the use of the majority voting method is more effective and efficient than one deep model.

The cause of improvement can be described as follows: Although each of the deep models can predict the disease COVID-19 alone, but the use of multiple convolution layers and various kernels that exist in pre-trained deep models, extract different features in different networks.

Therefore, in order to increase the accuracy of detection COVID-19, deep models are first performed alone, then their opinions are combined. One of the limitations of the proposed method is the use of MLP networks.

MLP networks used to recognize the real sample from the synthetic ones. Because of the lack of data in the minority class, MLPs might not be the best choice.

Regarding the advantages of the proposed method, it can be mention that: Although using the proposed architecture will give you better results, but it requires more time, which is one of the disadvantages of the method.

This issue can be considered in future studies. In the proposed model, synthetic samples are being generated in the feature space, in future work can used input space instead feature space. And in propose method we generated synthetic samples with MLP network.

We suggest using stronger, more diverse or a greater number of classifiers to solve this problem.

Author Contributions

I. Zabbah, K. Layeghi, and R. Ebrahimpour presented improving the Diagnosis of COVID-19 using a combination of Deep Learning Models. I. Zabbah examined each policy and wrote the manuscript. K. Layeghi and R. Ebrahimpour interpreted the results and improved the structure of paper.

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Conflict of Interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

Abbreviations

MLP	Multi-Layer Perceptron
SVM	Support Vector Machine
CNN	Convolution Neural Network
TL	Transfer Learning
CTS	Computed Tomography Scan

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