A Deep Learning Framework for Coronavirus Disease (COVID-19) Detection in X-Ray Images

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Research Article

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Abstract Coronavirus, a large family of viruses, causes illness in both humans and animals. The novel coronavirus (COVID-19) came up in Wuhan in December 2019. This deadly COVID-19 pandemic has become very fast-spreading and currently present in several countries worldwide. The timely detection of patients who have COVID-19 is vitally important. To this end, scientists are working on different detection methods. In this paper, a grid search (GS) and pre-trained model aided convolutional neural network (CNN) model is proposed to detect COVID-19 in X-Ray images. In the proposed method, the GS method is employed to optimize the hyperparameters of CNN, which directly affects classification performance. Three pre-trained CNN models (GoogleNet, ResNet18 and ResNet50), which can be used for classification, feature extraction and transfer learning purposes were used for transfer learning in this study. The proposed method was trained using the training and validation subdatasets of the collected dataset and detail evaluations are presented according to different performance metrics. According to the experimental studies, the best results were obtained with the GS and ResNet50 aided model.

Keywords COVID-19 detection · X-Ray images · Deep learning · CNN · Transfer learning · Hyperparameter optimization · Grid search

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1 Introduction

COVID-19 is a fast-spreading lethal coronavirus. It has spread all over the world in a very short time since it was initially detected in December 2019. Symptoms of this deadly include fever, dry cough and weakness [15]. The rapid and timely detection of sick individuals is important for both the patient's health and the prevention the further spread of the virus. COVID-19 diagnoses can be made by swabs from the nose and throat, blood count, computed tomography and X-Ray images.

Convolutional neural networks (CNNs), which have basic functions such as object recognition, classification and regression, has been popular in recent years. Some researchers have employed CNN for the detection of COVID-19. Wang and Wong [36] developed a COVID-NET with a deep CNN architecture for COVID-19 detection. They also presented the COVIDx dataset, which is adopted in this study. According to their experimental results, their proposed method produced good results.

A transfer learning-based CNN model that classifies medical data into three categories (normal, pneumonia, and Covid-19) has been proposed by Apostolopoulos and Bessiana [3]. In their study, which was carried out using five different pre-trained CNN models, they reported an accuracy of 98.75 % for the binary classification problem and 93.48 % for the multiclassification problem. Hemdan et al. [10] investigated COVIDX-19 classification with 7 different deep CNN architectures. In their experimental studies, they worked on two different categories, COVID-19 and non-COVID-19. Their dataset consisted of a total of 50 images. They reportedly achieved better results with the VGG19 and DenseNet201 models. Ghoshal

and Tucker [11] proposed a Dropweights based Bayesian Convolutional Neural Networks model and tested the proposed model for 4 different classes (normal, bacterial pneumonia, non-COVID-19 viral pneumonia and COVID-19). Sethy and Behera [32] extracted features from X-Ray images using pre-trained models. They collected their dataset from GitHub, Kaggle, and Open-I repository. According to their experimental results, features obtained from ResNet50 model and subsequently classified with SVM produced more successful results than the other models. A new deep learning aided anomaly detection model for COVID-19 detection from X-Ray images was proposed by Zhang et al. [39]. Their model achieved a sensitivity of 90.00% specificity of 87.84% when the threshold was set to 0.25. Narin et al. [21] proposed a transfer learning-based CNN model for detection of COVID-19. They used ResNet50, InceptionV3, and Inception-ResNetV2 pre-trained models for transfer learning. According to the results of their simulations, the ResNet50 based model recorded the best results.

As seen in the above literature review for COVID-19, the use of transfer learning based CNN is important to produce an effective model. Transfer learning supported CNN model has also used for different problems [24, 22, 26, 23, 6]. Similarly, pre-trained models have been used in the literature for different purposes besides transfer learning [1, 2, 4, 12, 35, 37].

The optimization of hyperparameters is an effective way to obtain higher success rates for machine learning methods. For this purpose, there is a plethora of studies in the literature. In addition to heuristic optimization algorithms [30, 17, 38, 8, 14, 25, 26, 24], the global search methods [31, 14, 29, 7] and other methods [9, 28] have also been used for hyperparameter optimization.

This study carries out the classification of COVID-19 from X-Ray images by using transfer learning-based CNN, whose hyperparameters were optimized by the GS method.

In the first stage, a dataset was created using X-Ray images collected from different platforms. This dataset includes bacteria, COVID-19, normal and virus classes. In the next stage, the proposed classification method was evaluated with the dataset and the detailed results are presented according to different performance metrics.

The main contributions of the paper are given below:

- In this paper, a transfer learning based CNN is proposed for COVID-19 detection on X-Ray

images. The hyperparameters of the generated CNN models are tuned by using the GS method. To the best of our knowledge, this study is the first in the literature that utilizes this approach for COVID-19 detection.

- The GS and ResNet18 aided method have the smallest computational time for parameter optimization.
- The GS and ResNet50 aided method obtained the best performance based on all of the metrics (accuracy, sensitivity, specificity, precision, and F1_score).

The remainder of this paper is organized as follows. The methodology including CNN, pre-trained models, GS, and the proposed method is given in Section 2. The experimental setup and results are provided in Section 3. Finally, Section 4 presents the conclusion and future works.

2 Methodology

In this paper, a deep learning model based unified method is presented for COVID-19 detection in X-Ray images. In the method section, convolutional neural networks (CNN) [18], which is a deep learning method, is used as the classifier and GoogleNet [34], ResNet18 [13], ResNet50 [13] pre-trained models are used for transfer learning. Additionally, a grid search method, which is a global search algorithm, is used for optimization of the the training settings of the generated CNN model. A detailed description is presented below.

2.1 Convolutional Neural Networks

CNN, which is a multi-layer neural network [19], is a type of artificial neural network and it is specialized to process big data [18]. A basic CNN structure usually has convolution, pooling, flattening, and fully connected layers. An example of a CNN architecture is presented in Fig. 1.

The convolution layer contains a set of learnable filters and is one of the structures in which the learning skill of CNN takes place [26]. An example of convolution operation is given in Fig. 2. Here, $\mathbf{I}$ refers to input image, $\mathbf{K}$ refers to filter and $\mathbf{I} * \mathbf{K}$ refers to feature map.

Another important structure that reduces the computational cost of a network is the pooling layer. Maximum, average and minimum pooling are the most frequently used pooling techniques [16]. An example of maxpooling operation is given in Fig. 3.

Fig. 1: The main layers of a CNN architecture

Fig. 2: An example of the convolution operation.

Fig. 3: An example of the maxpooling operation.

The fully connected layer comes after the both convolution and pooling layers of a CNN model [22]. Neurons in this layer have a full connection with the neurons in a previous layer. The data is flattened before coming to the fully connected layer. An example of a flattening operation is given in Fig. 4.

The training options of the CNN have an effect on its successful performance. Minibatch size, initial learning rate, ℓ_2 regularization parameter, and momentum value, which are optimized by GS in this paper, are some of the most important hyperparameters of a CNN model. The description of these hyperparameters are shown in Table 1.

Developing a new CNN model is a very challenging and time-consuming process. Using pre-trained models is a faster and more effective approach than

Fig. 4: An example of the flattening operation.

developing a new CNN model [23]. Pre-trained models are typically used for classification, transfer learning, and feature extraction. GoogleNet, ResNet18, and ResNet50 models were selected for transfer learning in this study. Some features of related pre-trained models are as shown in Table 2.

Table 2: Some features of the pre-trained models [20]

Model	Depth	Size	Parameters (Millions)	Image Input Size
GoogleNet	22	27 MB	7.0	224-by-224
ResNet18	18	44 MB	11.7	224-by-224
ResNet50	50	96 MB	25.6	224-by-224

2.2 Grid Search Algorithm

The grid search (GS) method used to optimize the parameters of a model is frequently preferred in applications where a short process of optimization is

Table 1: A brief description of the training options of a CNN model [24]

Option	Description	Value	Default	Type
Minibatch Size	Mini-batch size used for each training iteration.	Powers of 2 (Suggested)	128	Integer
Initial Learning Rate	Initial value of learning rate. If it is selected too low, training will take a long time, but if it is selected too high, the optimal result may not be found.	(0, 1)	0.01	Floating point
ℓ_2 regularization	Value of ℓ_2 regularizer. Each set of parameters in a layer can specify a multiplier for the ℓ_2 regularizer.	(0, 1)	0.0001	Floating point
Momentum	The contribution of the gradient step from the previous iteration to the current iteration	(0, 1)	0.90	Floating point

Fig. 5: Parameter sets in the search space for GS

desired. In GS, possible different values are determined in the related value ranges for a parameters. All combinations of these values (as shown in Fig. 5) are fed to the relevant model and the optimization process is started. The parameter set that gives the best results is determined and given as the output of the GS method.

2.3 Proposed Method

In this paper, a method including GS and transfer learning supported CNN model is proposed. The proposed method is given in Fig. 6. For the first step, the collected dataset is randomly split into three sub-datasets, which are training, validation, and testing. The training, validation, and testing sub-datasets are selected as 50%, 20%, and 30% of the dataset, respectively. For the next phase, parameter optimization using GS is realized. In this phase, the optimally selected hyperparameters from the parameter set table, and training data are given to the transfer learning supported CNN model as input. Afterwards, the model is trained using the training data and these parameters. A trained network is formed as an output. The trained network is evaluated on validation data using the Eq. 1. The computed

fitness function value (fval), and the hyperparameters are stored into a **table ???**. After the last loop of the parameter is realized, the best hyperparameters, which give the minimum fval value, are given as output of the parameter optimization phase. The best parameter set, training, and validation data are fed to the transfer learning CNN model. The final trained network serves as the output. Lastly, the trained network is evaluated on testing data and the result including all performance metrics is presented.

$$\text{fval} = 1 - \frac{\text{successful prediction count}}{\text{total sample count}} \quad (1)$$

3 Experimental Studies

In this section, the proposed method is applied on the collected dataset. The experimental setup is presented in Subsection 3.1 whereas the results of the proposed method are presented in Subsection 3.2.

3.1 Experimental Setup

The experimental setup phase was carried out before the main simulation stage. The data collection, parameter setup, environmental setup, and performance metrics are sub parts of this subsection.

3.1.1 Data Collection

Since the COVID-19 appeared in December 2019, it is quite difficult to obtain a public dataset for research work. Therefore, the data was obtained from different sources [5, 27] and hospital [33] shares. The number of samples for each class is given in Table 3.

3.1.2 Parameter Setup

The initial learning rate (ILR), ℓ_2 regularization (ℓ_2 R), momentum (Mom), and minibatch size (MiB) parameter values to be used in grid search are shown in Table 4.

Fig. 6: The GS and Pre-trained model aided method

Table 3: Overview of the number of samples for each category in the dataset.

	Bacteria	Covid-19	Normal	Virus
Train	121	66	100	74
Validation	48	26	40	30
Test	73	39	60	44
Total	242	131	200	148

Table 4: Parameter values used for GS

ILR	ℓ_2R	Mom	MiB
0.001	0.0001	0.85	8
0.005	0.001	0.90	16
0.010	0.005	0.95	32

3.1.3 Environmental Setup

An Nvidia GTX 1080 Ti Turbo with 11 GB Ram capacity was used for the experimental simulations.

3.1.4 Performance Metrics

Different types of metrics were used in order to evaluate performance for the proposed models. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are used to calculate

the metrics. Here, while TP refers to the correct predictions of COVID-19, TN refers to bacteria, normal or virus cases that were classified as non-COVID-19. Also, FP refers to bacteria, normal or virus cases that were classified as COVID-19. Lastly, FN refers to COVID-19 cases that classified as bacteria, normal or virus cases.

The performance metrics, which are accuracy, sensitivity (recall), specificity, precision, and F1-score, are calculated using Eq. 2-6, respectively.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

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

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$F1_score = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity} \quad (6)$$

Fig. 7: Sample images from collected dataset

3.2 Experimental Results

3.2.1 Parameter Optimization using GS for the Pre-trained Aided Model

In the proposed method, the GS algorithm is used to optimize the training parameters of the CNN model. When Table 8 is examined, all combinations of parameter sets and validation errors (fitness value, (fval)) of these parameter sets are presented for GoogleNet aided proposed method. The parameter values giving the error of 0,0278 are the best hyperparameters kept in the memory as a result of the GS approach.

All combinations of parameter sets and fvals of these parameter sets are presented in Table 9 for ResNet18 aided proposed method. The parameter values giving the error of 0,0208 are the best hyperparameters kept in the memory.

For the last method, ResNet50 aided proposed method, all combinations of parameter sets and fval values of these parameter sets are presented in Table 10. The parameter values giving the error of 0,0278 are the best hyperparameters.

3.2.2 General Results

The cost of computational time for parameter optimization using GS is given in Table 5. According to the table, less time is required for parameter optimization of the ResNet18 aided method.

Table 5: Time cost (sec.) for parameter optimization

GoogleNet	ResNet18	ResNet50
9675.1	8395.5	13374.9

While the optimal hyperparameters obtained by GS are presented in Table 6, the performance comparison of the proposed methods on the whole system is given in Table 7. When the results in the table is analyzed, the ResNet50 aided proposed method is the most successful one according to the metrics.

Table 6: The optimal hyperparameters selected by GS

Parameters	GoogleNet	ResNet18	ResNet50
ILR	0.0050	0.0100	0.0050
ℓ_2 R	0.0010	0.0050	0.0001
Mom	0.90	0.85	0.85
MiB	32	16	16

Table 7: Performance comparison of methods on whole system

Metric (%)	GoogleNet	ResNet18	ResNet50
Accuracy	93.98	97.22	97.69
Sensitivity	91.78	97.26	97.26
Specificity	95.10	97.20	97.90
Precision	90.54	94.67	95.95
F1_score	91.16	95.95	96.60

Table 8: Hyperparameters and fval values for the GS and GoogleNet aided method

Run	ILR	ℓ_2 R	Mom	MiB	fval
1	0.0010	0.0001	0.85	8	0.1319
2	0.0010	0.0001	0.85	16	0.0694
3	0.0010	0.0001	0.85	32	0.0556
4	0.0010	0.0001	0.90	8	0.0347
5	0.0010	0.0001	0.90	16	0.0833
6	0.0010	0.0001	0.90	32	0.0764
7	0.0010	0.0001	0.95	8	0.0486
8	0.0010	0.0001	0.95	16	0.0417
9	0.0010	0.0001	0.95	32	0.0417
10	0.0010	0.0050	0.85	8	0.0556
11	0.0010	0.0050	0.85	16	0.1042
12	0.0010	0.0050	0.85	32	0.1042
13	0.0010	0.0050	0.90	8	0.0694
14	0.0010	0.0050	0.90	16	0.0347
15	0.0010	0.0050	0.90	32	0.0486
16	0.0010	0.0050	0.95	8	0.0486
17	0.0010	0.0050	0.95	16	0.0903
18	0.0010	0.0050	0.95	32	0.0694
19	0.0010	0.0010	0.85	8	0.1181
20	0.0010	0.0010	0.85	16	0.0347
21	0.0010	0.0010	0.85	32	0.0764
22	0.0010	0.0010	0.90	8	0.0625
23	0.0010	0.0010	0.90	16	0.1944
24	0.0010	0.0010	0.90	32	0.0694
25	0.0010	0.0010	0.95	8	0.1111
26	0.0010	0.0010	0.95	16	0.1319
27	0.0010	0.0010	0.95	32	0.0625
28	0.0050	0.0001	0.85	8	0.2639
29	0.0050	0.0001	0.85	16	0.1319
30	0.0050	0.0001	0.85	32	0.0833
31	0.0050	0.0001	0.90	8	0.3403
32	0.0050	0.0001	0.90	16	0.0764
33	0.0050	0.0001	0.90	32	0.1389
34	0.0050	0.0001	0.95	8	0.6667
35	0.0050	0.0001	0.95	16	0.6667
36	0.0050	0.0001	0.95	32	0.1389
37	0.0050	0.0050	0.85	8	0.0764
38	0.0050	0.0050	0.85	16	0.0486
39	0.0050	0.0050	0.85	32	0.0903
40	0.0050	0.0050	0.90	8	0.1250
41	0.0050	0.0050	0.90	16	0.6667
42	0.0050	0.0050	0.90	32	0.1806
43	0.0050	0.0050	0.95	8	0.6667
44	0.0050	0.0050	0.95	16	0.5625
45	0.0050	0.0050	0.95	32	0.0556
46	0.0050	0.0010	0.85	8	0.1736
47	0.0050	0.0010	0.85	16	0.1528
48	0.0050	0.0010	0.85	32	0.1319
49	0.0050	0.0010	0.90	8	0.6181
50	0.0050	0.0010	0.90	16	0.0347
51	0.0050	0.0010	0.90	32	0.0278
52	0.0050	0.0010	0.95	8	0.6667
53	0.0050	0.0010	0.95	16	0.6667
54	0.0050	0.0010	0.95	32	0.1736
55	0.0100	0.0001	0.85	8	1.0000
56	0.0100	0.0001	0.85	16	0.5625
57	0.0100	0.0001	0.85	32	0.5972
58	0.0100	0.0001	0.90	8	1.0000
59	0.0100	0.0001	0.90	16	0.6667
60	0.0100	0.0001	0.90	32	0.5833
61	0.0100	0.0001	0.95	8	1.0000
62	0.0100	0.0001	0.95	16	0.6667
63	0.0100	0.0001	0.95	32	0.6667
64	0.0100	0.0050	0.85	8	0.6667
65	0.0100	0.0050	0.85	16	0.2778
66	0.0100	0.0050	0.85	32	0.1944
67	0.0100	0.0050	0.90	8	1.0000
68	0.0100	0.0050	0.90	16	0.6667
69	0.0100	0.0050	0.90	32	0.6181
70	0.0100	0.0050	0.95	8	1.0000
71	0.0100	0.0050	0.95	16	1.0000
72	0.0100	0.0050	0.95	32	0.6667
73	0.0100	0.0010	0.85	8	0.6667
74	0.0100	0.0010	0.85	16	0.4792
75	0.0100	0.0010	0.85	32	0.6667
76	0.0100	0.0010	0.90	8	1.0000
77	0.0100	0.0010	0.90	16	1.0000
78	0.0100	0.0010	0.90	32	1.0000
79	0.0100	0.0010	0.95	8	1.0000
80	0.0100	0.0010	0.95	16	0.6667
81	0.0100	0.0010	0.95	32	0.6667

Table 9: Hyperparameters and fval values for the GS and ResNet18 aided method

Run	ILR	ℓ_2 R	Mom	MiB	fval
1	0.0010	0.0001	0.85	8	0.0556
2	0.0010	0.0001	0.85	16	0.0556
3	0.0010	0.0001	0.85	32	0.0556
4	0.0010	0.0001	0.90	8	0.0556
5	0.0010	0.0001	0.90	16	0.0694
6	0.0010	0.0001	0.90	32	0.0764
7	0.0010	0.0001	0.95	8	0.0347
8	0.0010	0.0001	0.95	16	0.0694
9	0.0010	0.0001	0.95	32	0.0486
10	0.0010	0.0050	0.85	8	0.0694
11	0.0010	0.0050	0.85	16	0.1042
12	0.0010	0.0050	0.85	32	0.1042
13	0.0010	0.0050	0.90	8	0.0764
14	0.0010	0.0050	0.90	16	0.0625
15	0.0010	0.0050	0.90	32	0.0764
16	0.0010	0.0050	0.95	8	0.0486
17	0.0010	0.0050	0.95	16	0.0556
18	0.0010	0.0050	0.95	32	0.0556
19	0.0010	0.0010	0.85	8	0.0833
20	0.0010	0.0010	0.85	16	0.0694
21	0.0010	0.0010	0.85	32	0.8194
22	0.0010	0.0010	0.90	8	0.0694
23	0.0010	0.0010	0.90	16	0.0764
24	0.0010	0.0010	0.90	32	0.0694
25	0.0010	0.0010	0.95	8	0.0556
26	0.0010	0.0010	0.95	16	0.0556
27	0.0010	0.0010	0.95	32	0.0417
28	0.0050	0.0001	0.85	8	0.0556
29	0.0050	0.0001	0.85	16	0.0486
30	0.0050	0.0001	0.85	32	0.0625
31	0.0050	0.0001	0.90	8	0.0625
32	0.0050	0.0001	0.90	16	0.0556
33	0.0050	0.0001	0.90	32	0.0625
34	0.0050	0.0001	0.95	8	0.1319
35	0.0050	0.0001	0.95	16	0.0764
36	0.0050	0.0001	0.95	32	0.0417
37	0.0050	0.0050	0.85	8	0.0417
38	0.0050	0.0050	0.85	16	0.0556
39	0.0050	0.0050	0.85	32	0.0694
40	0.0050	0.0050	0.90	8	0.0417
41	0.0050	0.0050	0.90	16	0.8194
42	0.0050	0.0050	0.90	32	0.0556
43	0.0050	0.0050	0.95	8	0.0833
44	0.0050	0.0050	0.95	16	0.0556
45	0.0050	0.0050	0.95	32	0.0486
46	0.0050	0.0010	0.85	8	0.0417
47	0.0050	0.0010	0.85	16	0.0625
48	0.0050	0.0010	0.85	32	0.0486
49	0.0050	0.0010	0.90	8	0.0694
50	0.0050	0.0010	0.90	16	0.0486
51	0.0050	0.0010	0.90	32	0.0556
52	0.0050	0.0010	0.95	8	0.1458
53	0.0050	0.0010	0.95	16	0.0625
54	0.0050	0.0010	0.95	32	0.0556
55	0.0100	0.0001	0.85	8	0.0556
56	0.0100	0.0001	0.85	16	0.0417
57	0.0100	0.0001	0.85	32	0.0556
58	0.0100	0.0001	0.90	8	0.1458
59	0.0100	0.0001	0.90	16	0.0625
60	0.0100	0.0001	0.90	32	0.0347
61	0.0100	0.0001	0.95	8	0.0903
62	0.0100	0.0001	0.95	16	0.1111
63	0.0100	0.0001	0.95	32	0.0556
64	0.0100	0.0050	0.85	8	0.8194
65	0.0100	0.0050	0.85	16	0.0208
66	0.0100	0.0050	0.85	32	0.0556
67	0.0100	0.0050	0.90	8	0.1319
68	0.0100	0.0050	0.90	16	0.8194
69	0.0100	0.0050	0.90	32	0.0833
70	0.0100	0.0050	0.95	8	0.1597
71	0.0100	0.0050	0.95	16	0.0625
72	0.0100	0.0050	0.95	32	0.0764
73	0.0100	0.0010	0.85	8	0.1111
74	0.0100	0.0010	0.85	16	0.0556
75	0.0100	0.0010	0.85	32	0.0486
76	0.0100	0.0010	0.90	8	0.0972
77	0.0100	0.0010	0.90	16	0.0417
78	0.0100	0.0010	0.90	32	0.0556
79	0.0100	0.0010	0.95	8	0.1875
80	0.0100	0.0010	0.95	16	0.1389
81	0.0100	0.0010	0.95	32	0.0556

Table 10: Hyperparameters and fval values for the GS and ResNet50 aided method

Run	ILR	ℓ_2 R	Mom	MiB	fval
1	0.0010	0.0001	0.85	8	0.0972
2	0.0010	0.0001	0.85	16	0.0625
3	0.0010	0.0001	0.85	32	0.0556
4	0.0010	0.0001	0.90	8	0.8194
5	0.0010	0.0001	0.90	16	0.0486
6	0.0010	0.0001	0.90	32	0.0625
7	0.0010	0.0001	0.95	8	0.0486
8	0.0010	0.0001	0.95	16	0.0694
9	0.0010	0.0001	0.95	32	0.0625
10	0.0010	0.0050	0.85	8	0.0694
11	0.0010	0.0050	0.85	16	0.0694
12	0.0010	0.0050	0.85	32	0.0764
13	0.0010	0.0050	0.90	8	0.0486
14	0.0010	0.0050	0.90	16	0.0417
15	0.0010	0.0050	0.90	32	0.0694
16	0.0010	0.0050	0.95	8	0.0625
17	0.0010	0.0050	0.95	16	0.0556
18	0.0010	0.0050	0.95	32	0.0764
19	0.0010	0.0010	0.85	8	0.0833
20	0.0010	0.0010	0.85	16	0.0694
21	0.0010	0.0010	0.85	32	0.0625
22	0.0010	0.0010	0.90	8	0.0556
23	0.0010	0.0010	0.90	16	0.0625
24	0.0010	0.0010	0.90	32	0.0903
25	0.0010	0.0010	0.95	8	0.0486
26	0.0010	0.0010	0.95	16	0.0694
27	0.0010	0.0010	0.95	32	0.0486
28	0.0050	0.0001	0.85	8	0.0347
29	0.0050	0.0001	0.85	16	0.0278
30	0.0050	0.0001	0.85	32	0.0625
31	0.0050	0.0001	0.90	8	0.0486
32	0.0050	0.0001	0.90	16	0.0625
33	0.0050	0.0001	0.90	32	0.0694
34	0.0050	0.0001	0.95	8	0.0764
35	0.0050	0.0001	0.95	16	0.0694
36	0.0050	0.0001	0.95	32	0.0556
37	0.0050	0.0050	0.85	8	0.0417
38	0.0050	0.0050	0.85	16	0.0417
39	0.0050	0.0050	0.85	32	0.0764
40	0.0050	0.0050	0.90	8	0.0417
41	0.0050	0.0050	0.90	16	0.0625
42	0.0050	0.0050	0.90	32	0.0625
43	0.0050	0.0050	0.95	8	0.0694
44	0.0050	0.0050	0.95	16	0.0764
45	0.0050	0.0050	0.95	32	0.0417
46	0.0050	0.0010	0.85	8	0.0486
47	0.0050	0.0010	0.85	16	0.0486
48	0.0050	0.0010	0.85	32	0.0625
49	0.0050	0.0010	0.90	8	0.0278
50	0.0050	0.0010	0.90	16	0.0486
51	0.0050	0.0010	0.90	32	0.0486
52	0.0050	0.0010	0.95	8	0.0833
53	0.0050	0.0010	0.95	16	0.0486
54	0.0050	0.0010	0.95	32	0.0347
55	0.0100	0.0001	0.85	8	0.0417
56	0.0100	0.0001	0.85	16	0.0486
57	0.0100	0.0001	0.85	32	0.0486
58	0.0100	0.0001	0.90	8	0.8194
59	0.0100	0.0001	0.90	16	0.0833
60	0.0100	0.0001	0.90	32	0.0625
61	0.0100	0.0001	0.95	8	0.1875
62	0.0100	0.0001	0.95	16	0.1667
63	0.0100	0.0001	0.95	32	0.0486
64	0.0100	0.0050	0.85	8	0.0347
65	0.0100	0.0050	0.85	16	0.0417
66	0.0100	0.0050	0.85	32	0.0486
67	0.0100	0.0050	0.90	8	0.1597
68	0.0100	0.0050	0.90	16	0.0486
69	0.0100	0.0050	0.90	32	0.0694
70	0.0100	0.0050	0.95	8	0.8194
71	0.0100	0.0050	0.95	16	0.0625
72	0.0100	0.0050	0.95	32	0.0972
73	0.0100	0.0010	0.85	8	0.0694
74	0.0100	0.0010	0.85	16	0.8194
75	0.0100	0.0010	0.85	32	0.0556
76	0.0100	0.0010	0.90	8	0.0417
77	0.0100	0.0010	0.90	16	0.0347
78	0.0100	0.0010	0.90	32	0.0903
79	0.0100	0.0010	0.95	8	0.1111
80	0.0100	0.0010	0.95	16	0.0833
81	0.0100	0.0010	0.95	32	0.0694

Fig. 8: The confusion matrix for GoogleNet on test data

Fig. 9: The confusion matrix for ResNet18 on test data

Fig. 10: The confusion matrix for ResNet50 on test data

The confusion matrices which are formed according to the accuracy performance of the proposed methods are presented in Fig. 8 - 10. In addition, the training progress graphics for the final training processes of the proposed methods are given in Fig. 11 - 13, respectively.

Fig. 11: Training progress for GoogleNet aided method

Fig. 12: Training progress for ResNet18 aided method

Fig. 13: Training progress for ResNet50 aided method

4 Conclusion

COVID-19 is a deadly virus that currently impacting the entire world. The early detection of this virus provides both a slowing down of the outbreak and the recovery of the diagnosed patients more quickly. Recently, deep learning methods are frequently used in classification problems. Additionally, the performance of deep learning methods is implemented by a hyperparameter selection. In this study, a classification system was developed by using both the GS and pre-trained CNN models. Here, while GS was used for hyperparameter optimization, the pre-trained models were used for transfer learning. With the proposed method, classification experiments were carried for 4 different classes on X-Ray images of the lungs. These categories of the dataset include bacteria, COVID-19, normal, and virus. In the proposed method, 3 different pre-trained models (GoogleNet, ResNet18, ResNet50) were used. The highest accuracy rate (97.69%) was obtained with the GS and ResNet50 aided proposed method.

In future studies, different pre-trained models will be used for transfer learning. Additionally, different global search methods would be employed for hyperparameter optimization.

Conflict of interest

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Figures

Figure 1

The main layers of a CNN architecture

Figure 2

An example of the convolution operation.

Figure 3

An example of the maxpooling operation.

Figure 4

An example of the attening operation.

Figure 5

Parameter sets in the search space for GS

Figure 6

The GS and Pre-trained model aided method

Figure 7

Sample images from collected dataset

Figure 8

The confusion matrix for GoogleNet on test data

Figure 9

The confusion matrix for ResNet18 on test data

Figure 10

The confusion matrix for ResNet50 on test data

Figure 11

Training progress for GoogleNet aided method

Figure 12

Training progress for ResNet18 aided method

Figure 13

Training progress for ResNet50 aided method