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# ECG-COVID: An end-to-end deep model based on electrocardiogram for COVID-19 detection

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## ABSTRACT

The early and accurate detection of COVID-19 is vital nowadays to avoid the vast and rapid spread of this virus and ease lockdown restrictions. As a result, researchers developed methods to diagnose COVID-19. However, these methods have several limitations. Therefore, presenting new methods is essential to improve the diagnosis of COVID-19. Recently, investigation of the electrocardiogram (ECG) signals becoming an easy way to detect COVID-19 since the ECG process is non-invasive and easy to use. Therefore, we proposed in this paper a novel end-to-end deep learning model (ECG-COVID) based on ECG for COVID-19 detection. We employed several deep Convolutional Neural Networks (CNNs) on a dataset of 1109 ECG images, which is built for screening the perception of COVID-19 and cardiac patients. After that, we selected the most efficient model as our model for evaluation. The proposed model is end-to-end where the input ECG images are fed directly to the model for the final decision without using any additional stages. The proposed method achieved an average accuracy of 98.81%, Precision of 98.8%, Sensitivity of 98.8% and, F1-score of 98.81% for COVID-19 detection. As cases of corona continue to rise and hospitalizations continue again, hospitals may find our study helpful when dealing with these patients who did not get significantly worse.

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## 1. Introduction

Public health is seriously threatened by the Coronavirus (COVID-19) pandemic which represents a major economic challenge for countries around the world [1]. In order to address these challenges, artificial intelligence-based Computer-aided diagnosis (CAD) systems, technologies, and related products have emerged to support the first efforts for epidemic prevention and control. In March 2020, as the virus began to move around the world, the demand for the technology needed to

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tackle COVID-19 began to increase daily in many countries. Therefore, building CAD systems for the detection of COVID-19 is vital to save human lives.

Recently, experts have come up with a new vital number that can be measured using an electrocardiogram (ECG), as this vital number can predict the death of a patient due to complications from corona at least two days before [2]. The ECG shows a graph showing the shape of ripples that are directly related to the movement of the heart's electricity during its work. These waves are divided into sections defined by the following letters: P, QRS, and T. The letter P stands for the movement of electricity during the work of the upper molecule of the heart, and QRS for the creation of the lower molecule. At the same time, T relates to the movement of electricity during the resting period of the heart muscle.

An investigation of the health records of 140 patients with corona revealed that the decrease in QRS waveforms was a sign of the patient's decline in around 70 % of cases [3]. The standards established by a team at Mount Sinai Hospital in New York are called low QRS (LoQRS) [4]. Therefore, the researchers suggest that this indicator could be an effective way to triage patients whose health conditions are most probable to decline. The study found a 52-hour mean time to death after the first LoQRS reading was detected [5]. Studies have shown that gradual decreases in waveforms on the ECG may be an important indicator of rapid clinical changes with COVID-19 disease, allowing health care workers to intervene more promptly during the hospital stay for these patients [6,7]. Therefore, using ECG for developing a CAD system to detect COVID-19 becomes vital. To our knowledge, there are very few studies that used ECG for developing a CAD system for COVID detection [8–10,30–34]. However, these studies work on complex models, which increase the cost complexity of the system. In addition, these studies also used separate classifiers, which increase the possibility of overfitting and also need to be suitable for the extracted features to obtain high accuracy. In this study, we overcome the problems of previous studies by proposing an end-to-end deep learning model called ECG-COVID, which decreases the cost of the system. The main novel contributions of this study are:

- Propose a new end-to-end deep model called ECG-COVID based on ECG for the detection of COVID-19. The proposed method consists of only one stage where the input ECG image is fed directly to the proposed model, which decreases the complexity of the system and makes the system cost-effective.
- Propose an efficient method, which can detect COVID-19 in a little time. Unlike other previous methods that used separate classifiers for classification, which need to select adapted with the extracted features.
- We thoroughly evaluated several deep models through a set of experiments, and the obtained results outline the merits and demerits of these models. The main parts of our code were uploaded at: <https://github.com/assakr/covid-ECG/blob/main/deep%20ecg%20covid>

## 2. Related work

Several previous studies used artificial intelligence approaches to analyze and classify the ECG signals in different medical applications [11–14]. Some of these studies presented methods for the classification of ECG signals to normal and abnormal signals [11,12]. Other studies focused on classifying ECG images as normal and other cardiac abnormalities [13,14]. These methods previously employed conventional machine learning techniques. However, recently, the studies focused on employing deep learning approaches to classify ECG [15–20] as deep learning can overcome most previous traditional problems and also obtain high accuracy with big data. Therefore, we employed a deep learning approach in this study.

Recently, we were affected by new Coronavirus or COVID-19, which affect the industrial fields and income in general. In addition, the effect of this virus may lead to death. Therefore, finding a way to detect this virus early is vital. However, the method to detect this virus is costly and needs time. So, the researchers have searched for another method that can be fast and less in cost [35]. Finally, in [21] the authors prove that COVID can affect the ECG signals, and the difference between the normal ECG and COVID ECG can appear obviously on the signal. As a result, researchers have started working on this point to detect the COVID from ECG. As this method is recently proven so the work using this method is very few. For example, Attallah [8], tested the ability to employ ECG data to detect Covid-19. The author used five deep learning pre-trained models and two levels of features from several layers are extracted from each model. Discrete wavelet transform (DWT) is used to fuse feature mined from higher layers before integrating with lower-layer features. Finally, an ensemble classifier is developed to merge the prediction of several machine learnings classifier with 98.8 % accuracy for the binary category and multi-category with 91.73 % accuracy. Rahman *et al* [9], used ECG dataset of five categories, including covid-19 to explore the possibility of employing ECG Data to detect COVID-19. They used six deep CNN models to investigate three classification category-one binary classification with an accuracy 99.1 % and two multi-classification one with three classes with accuracy of 97.26 %, and the other of five class with accuracy 97.83 %. Ozdamer *et al* [10], presented an automatic diagnosis of COVID-19 based on ECG using deep learning. They introduced a method called Hexal feature mappings to represent ECG data to 2D images. Gray-Level Co-occurrence matrix is employed for feature extraction, then the extracted image is fed into CNN for COVID-19 detection. They obtained an accuracy of 96.2 % and F1-score of 96.3 % for binary classification and an accuracy of 93 % and F1-score of 93.2 % for multi-classification. Emrah [31] presented a model based on CNN for COVID-19 and abnormal ECG classification. Their CNN model consisted of feature extraction and classification stages. They used the same VGG-16 architecture and obtained an accuracy of 98.57 % for classification. Attallah [32] introduced a tool based on ECG for COVID-19 detection. The author used 10 pre-train deep learning models combining together with assemble classifier for classification. They obtained an accuracy of 98.20 % for classification.

From the discussion previously, we can observe that all of the related works used transfer learning techniques. It is important to point out that transfer learning does not work for every issue since it only works if the target problem and the initial one are sufficiently similar for the first round of training to be relevant. In addition, removing layers with assurance reduces the number of parameters being problematic. Moreover, using pre-trained models also have several disadvantages such as:

- Increased the complexity of architecture in some deep models.
- Totally depending on the implementation of batch normalization layers such as ResNet model heavily depend on these layers.
- Adding skip level connections for which taking into account the dimensionality between the different layers can become a problem.

Although the DWT has several serious drawbacks, including shift sensitivity, poor directionality, and the absence of phase information. The proposed model is end-to-end and does not need any external stages such as other previous work, which decreases the complexity of our model. In addition, our model is simple and established from scratch with few layers than other deep models in previous work that used pre-trained models with several layers that lead to increases the processing time.

### 3. Methods and materials

In this Section, we discuss the datasets used in this study in detail. In addition, we discuss all steps of the proposed deep learning method in detail.

#### 3.1. Dataset description

In this study, we worked on a dataset which is built for screening the perception of COVID-19 and Cardiac patients [21]. This dataset consists of 12-lead ECG images gathered from different patients from various cardiac institutes across Pakistan. In this study, we worked on lead II ECG image to reduce the complexity and also all-important information that appears in this lead. The number of COVID-19 patients is 250 ECG images and the number of normal persons is 859 ECG images with sampling rate of 500 Hz. In the train set, there were 190 ECG images for COVID-19 and 697 ECG images for normal persons. In the validation set, there are 111 images in total where 30 for COVID-19 and 81 for normal. The test set also has 30 for COVID-19 and 81 for normal. Fig. 1 shows sample of ECG images for COVID-19 and normal.

#### 3.2. Performance measurement

In order to measure the performance of our method - accuracy, sensitivity or recall, F1-score, precision and Receiver Operating Characteristic (ROC) are employed. These measurements are calculated according to the following equations:

$$\text{accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (2)$$

$$\text{precision} = \frac{TP}{TP + FP} \quad (3)$$

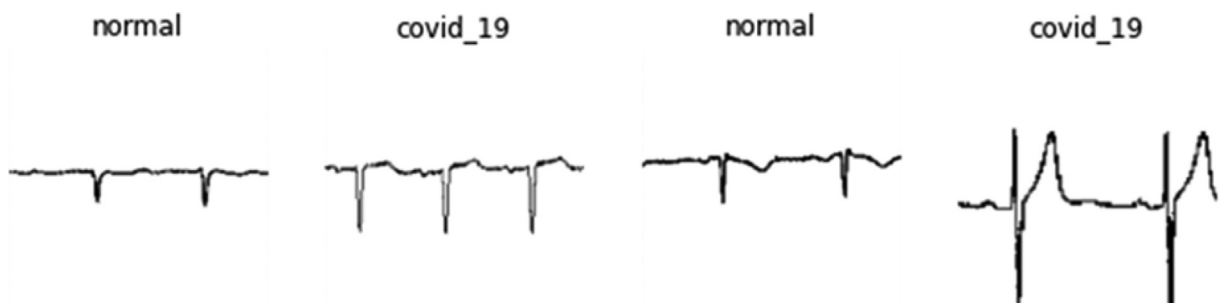


Fig. 1. Sample of ECG images collected from the dataset [21].

$$F1 - score = 2 \times \frac{recall \times precision}{recall + precision} \quad (4)$$

where,  $TP$ ,  $TN$ ,  $FP$ , and  $FN$  denote the number of true positive, true negative, false positive, and false-negative samples, respectively.

ROC curve plots the TP rate versus the FP rate of a binary classification problem.

### 3.3. Proposed approach

The general block diagram of the ECG-COVID method is presented in Fig. 2. The proposed method is end-to-end where the input ECG image is directly fed to the model for final decision. We build several convolution neural network (CNN) deep models from scratch to perform the detection, where the feature extraction and classification are combined in these models. After that, we selected the efficient model to be our model. CNN is the common type of deep learning model, which is used in different applications [22–28]. CNN model consists of several layers a part of these layers is used as a feature extractor to extract the deep features of input images whereas another part is used for classification. These layers are named convolutional, pooling, fully connected, and SoftMax layers. In our case, unlike all other previous studies that used pre-trained models, we establish several CNN models from scratch and we selected the best model among these models. In each model, we choose the optimizers. Adam as an optimizer [29] and losses. SparseCategoricalCrossentropy as a loss function. In addition, we set the min batch size = 4 and each model will stop after 30 epochs.

#### 3.3.1. The first CNN model

In this model, we start with 4 convolution layers and each layer is followed by max pooling layer. After that, we add flatten layer followed by 2 dense layers with total of 4,063,138 parameters. Before feeding the input ECG images to the model, we resize all images to be  $180 \times 180$ . The structure of this model with the output shape and number of parameters in each layer is shown in Fig. 3.

From Fig. 3, we can find that employing max pooling layer after each convolutional layer reduced the size of the input image, which reduced the time and cost complexity of the model. After that, flatten layer is added to convert the two-dimension features to one vector features, which makes it suitable for classification. Moreover, there is a dense layer with 256 units with ReLU activation function. Finally, the SoftMax layer, which is the most common layer in deep models that are used for classification, is used for the final decision of our model.

#### 3.3.2. The second CNN model

In this model, we start with 6 convolution layers followed by max pooling layers (similar to the first model) except the first two convolution layers are followed with only one max pooling. After that, we add flatten layer followed by 2 dense layers with total of 2,034,098 parameters, which is less than the first model. Before feeding the input ECG images to the model, we resize all images to be  $180 \times 180$ . The structure of this model with the output shape and number of parameters in each layer is shown in Fig. 4.

From Fig. 4, we can find that employing more convolutional layers makes the model deeper unlike the first model, which is implemented with few layers than this model. As a result, obtain deep features and more details from the input images, which is useful in case of COVID-19 images that have more noise than normal ECG images. After that, flatten layer is added to convert the two-dimension features as in the first model but with less parameter than the first mode with the same fully

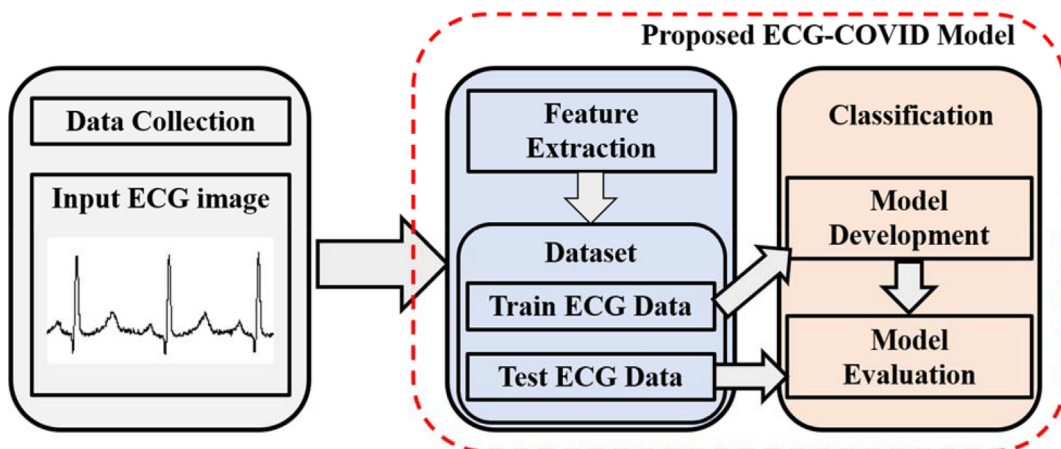


Fig. 2. Block Diagram of ECG-COVID Model.

Layer (type)	Output Shape	Param #
rescaling_6 (Rescaling)	(None, 180, 180, 3)	0
conv2d_12 (Conv2D)	(None, 180, 180, 16)	448
max_pooling2d_12 (MaxPooling2D)	(None, 90, 90, 16)	0
conv2d_13 (Conv2D)	(None, 90, 90, 32)	4640
max_pooling2d_13 (MaxPooling2D)	(None, 45, 45, 32)	0
conv2d_14 (Conv2D)	(None, 45, 45, 64)	18496
max_pooling2d_14 (MaxPooling2D)	(None, 22, 22, 64)	0
conv2d_15 (Conv2D)	(None, 22, 22, 128)	73856
max_pooling2d_15 (MaxPooling2D)	(None, 11, 11, 128)	0
flatten_3 (Flatten)	(None, 15488)	0
dense_6 (Dense)	(None, 256)	3965184
dense_7 (Dense)	(None, 2)	514
Total params: 4,063,138		
Trainable params: 4,063,138		
Non-trainable params: 0		

Fig. 3. Structure of the first CNN model.

connected and the same SoftMax layer. This model achieved the highest performance comparing with other models. As a result, in our study, we selected this model for evaluation and for comparison with other methods.

### 3.3.3. The third CNN model

In this model, we start with 6 convolution layers followed by max pooling layers (similar to the second model) except the first three convolution layers are followed with only one max pooling. After that, we add flatten layer followed by 1 dropout layer and 2 dense layers with total 8,325,554 parameters, which is more than the first and the second model. Before feeding the input ECG images to the model, we resize all images to be  $180 \times 180$ . The dropout layer is added to overcome the overfitting problem (if there is a difference in accuracy between training and validation accuracy can be noticeable). The structure of this model with the output shape and number of parameters in each layer is shown in Fig. 5.

From Fig. 5, we can find that the number of convolutional layers is equal to the number of convolutional layers in the second model, however, the max pooling layers in this model is less than the second model. As a result, effect on the size of input image and the time and cost complexity. In addition, the number of parameters is more than the second model which increase the computational process of the model.

### 3.3.4. ECG-COVID model

According to the results of our study, we have considered the second model being our model for evaluation and for comparison with other previous methods. This model consists of 5 blocks. The first block consists of 2 convolution layers followed by one max pooling layer. The blocks from 2 to 5 are the same which consist of 1 convolution layer followed by one max pooling layer. After that, the classification layer, which is consisting of a Flatten layer followed by 2 dense layers. The complete architecture of the proposed model is illustrated in Fig. 6. In this model, ReLU activation function is employed to decide whether a neuron works or not. The ReLU function is chosen to avoid overfitting and increase computational speed and given by:

Layer (type)	Output Shape	Param #
rescaling_4 (Rescaling)	(None, 180, 180, 3)	0
conv2d_16 (Conv2D)	(None, 180, 180, 16)	448
conv2d_17 (Conv2D)	(None, 180, 180, 16)	2320
max_pooling2d_14 (MaxPooling2D)	(None, 90, 90, 16)	0
conv2d_18 (Conv2D)	(None, 90, 90, 32)	4640
max_pooling2d_15 (MaxPooling2D)	(None, 45, 45, 32)	0
conv2d_19 (Conv2D)	(None, 45, 45, 64)	18496
max_pooling2d_16 (MaxPooling2D)	(None, 22, 22, 64)	0
conv2d_20 (Conv2D)	(None, 22, 22, 128)	73856
max_pooling2d_17 (MaxPooling2D)	(None, 11, 11, 128)	0
conv2d_21 (Conv2D)	(None, 11, 11, 256)	295168
max_pooling2d_18 (MaxPooling2D)	(None, 5, 5, 256)	0
flatten_3 (Flatten)	(None, 6400)	0
dense_6 (Dense)	(None, 256)	1638656
dense_7 (Dense)	(None, 2)	514
Total params: 2,034,098		
Trainable params: 2,034,098		
Non-trainable params: 0		

Fig. 4. Structure of the second CNN model.

$$y = \max(0, x) \quad (5)$$

where  $x$  refers to the input of the neuron. In addition, the kernel size is set to  $3 \times 3$  for each convolution layer in our model. We employed the SoftMax layer as a classification layer. The SoftMax layer utilizes the SoftMax function to obtain the classification results and given by:

$$\text{Softmax}(y_i) = y'_i = \frac{e^{y_i}}{\sum_{j=1}^n e^{y_j}} \quad (6)$$

where  $y_i$  is the  $i_{th}$  value from the output of the last layer, and  $y'_i$  refers to the output probability vector.

#### 4. Results

In this Section, *two* sets of experiments are designed. In the first experiment, we trained and compared *three* CNN architectures on the dataset. In the second experiment, we compared the efficient model from the experiment one with other previous methods on the dataset. The proposed model was implemented using python 3 software on HP ZBook Fury 15 G7 Mobile Workstation with 10th Generation Intel® Core™ i9 processor and 64 GB DDR4.



Layer (type)	Output Shape	Param #
rescaling_6 (Rescaling)	(None, 180, 180, 3)	0
conv2d_28 (Conv2D)	(None, 180, 180, 16)	448
conv2d_29 (Conv2D)	(None, 180, 180, 16)	2320
conv2d_30 (Conv2D)	(None, 180, 180, 32)	4640
max_pooling2d_23 (MaxPoolin g2D)	(None, 90, 90, 32)	0
conv2d_31 (Conv2D)	(None, 90, 90, 64)	18496
max_pooling2d_24 (MaxPoolin g2D)	(None, 45, 45, 64)	0
conv2d_32 (Conv2D)	(None, 45, 45, 128)	73856
max_pooling2d_25 (MaxPoolin g2D)	(None, 22, 22, 128)	0
conv2d_33 (Conv2D)	(None, 22, 22, 256)	295168
max_pooling2d_26 (MaxPoolin g2D)	(None, 11, 11, 256)	0
flatten_5 (Flatten)	(None, 30976)	0
dropout_1 (Dropout)	(None, 30976)	0
dense_10 (Dense)	(None, 256)	7930112
dense_11 (Dense)	(None, 2)	514
Total params: 8,325,554		
Trainable params: 8,325,554		
Non-trainable params: 0		

Fig. 5. Structure of the third CNN model.

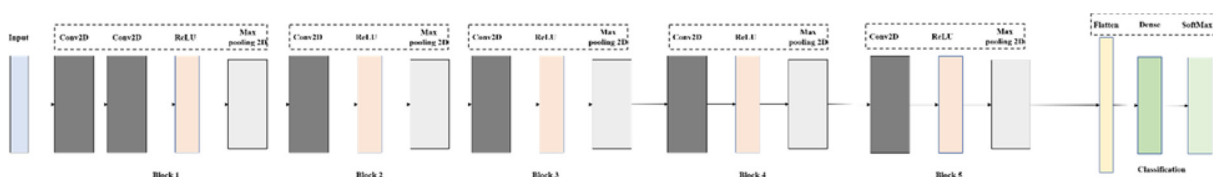


Fig. 6. The architecture of ecg-covid model.

#### 4.1. Performance of CNN architectures

We trained and compared three CNN architectures on the dataset. Fig. 7 demonstrates the validation and training accuracy and loss for the first model.

It can be observed that after 10 epochs, the improvements are marginal and after 20 epochs, the model can be considered fully trained.

The validation and training losses and accuracies of the second model are demonstrated in Fig. 8.

Similar behavior can be observed for the second model as well. The model improves marginally after 10 epochs, and after 20 epochs, the model can be considered fully trained.





Fig. 7. Validation and training loss and accuracy for first model.



Fig. 8. Validation and training loss and accuracy for second model.

Fig. 9 demonstrates the validation and training losses and accuracies, respectively, for the third model.

It can be observed from the figure that substantial improvements are obtained until the 10th epoch. After 20 epochs, the training losses and accuracies remain constant and the validation metrics also do not improve. Therefore, the model can be considered fully trained at this point.

Table 1 shows the results of the three models in terms of accuracy, precision, sensitivity and F1-score.

From Table 1, we can see that Model 2 achieved the highest Accuracy, Precision, Sensitivity, and F1-score. Model 3 performs slightly worse than Model 2 in terms of all of these evaluation metrics. Model 1, which has a lower number of con-



Fig. 9. Validation and training loss and accuracy for third model.

**Table 1**

Model performance.

Model number	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)
Model 1	96.53	96.53	96.53	96.53
Model 2	98.81	98.81	98.81	98.81
Model 3	97.20	97.20	97.20	97.20

volitional layers is the worst performance compared with other models. As a result, we selected Model 2 as our model (the ECG-COVID), which obtained the highest performance compared with other models.

We employed 10-fold and 5-fold cross validation techniques for our experiments, which are the same experimental protocol for the previous related work to make a fair comparison. Tables 2 and 3 represent the results of the selected model using 5-fold and 10-fold algorithms, respectively.

## 5. Discussion

The results of the Figures from 7 to 9 and Table 1 are shown that the efficient model is the second model, therefore, we selected this model as the proposed model (ECG-COVID). Also, from the results, we can observe that using small number of convolutional layers decreases the overall accuracy of the system as in Model 1 (the worst accuracy). In addition, using small number of max pooling layers lead to low accuracy and high number of parameters (as in Model 1 and 3). In the second Model, we employed 6 convolutional layers (more than Model 1) with 5 max pooling layers which are more than Models 1 and 3. However, increasing the convolutional layers (more than the number in Model 2) make the system fall and

**Table 2**

The results of our model using 5-fold cross validation.

Folds	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)	Elapsed time (second)
1	99.66	99.66	99.66	99.66	25.982345342636
2	99.33	99.33	99.33	99.33	24.033320665359
3	99.99	99.99	99.99	99.99	24.099491834640
4	98.50	98.50	98.50	98.50	24.053133010864
5	94.99	94.99	94.99	94.99	24.238087654113

Avg Accuracy = 98.49 %.

Best Accuracy = 99.99 %.

Standard deviation = 2.03559.

**Table 3**

The results of our model using 10-fold cross validation.

Folds	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)	Elapsed time (second)
1	99.95	99.95	99.95	99.95	30.639287710189
2	96.14	96.17	96.17	96.17	28.308854579925
3	93.47	93.52	93.52	93.52	28.567873239517
4	99.98	99.98	99.98	99.98	28.667985439300
5	91.29	91.37	91.37	91.37	28.646018743515
6	90.50	90.58	90.58	90.58	28.826886415481
7	93.87	93.94	93.94	93.94	28.189328193664
8	96.73	96.76	96.76	96.76	28.272521495819
9	92.87	92.94	92.94	92.94	27.962646245956
10	94.36	94.41	94.41	94.41	28.141548156738

Avg Accuracy = 94.91 %.

Best Accuracy = 99.98 %.

Standard deviation = 3.26774.

decreases the overall accuracy of the system. Furthermore, from [Tables 2 and 3](#) we can observe that, the proposed model using K-fold strategy achieved acceptable average accuracy with high accuracy in most folds. From the Tables, the average accuracies using 5 and 10 folds are 98.49 % and 94.91 %, respectively and the best accuracies are 99.99 % and 99.98 %, respectively.

### 5.1. Controlling the stability of the proposed model using the batch size

The batch size is used to control the accuracy of gradient error estimation when training the model. In our experiments, we employed the min batch-size = 4 as we find that this is the most suitable for the proposed model and achieved the highest accuracy. We have refitted our model with different min batch sizes and observe the impact of changes. [Figs. 10, 11 and 12](#) show the validation and training losses and accuracies of the proposed model in case of using different batch sizes (32, 16 and 8).

From the previous Figures, we can observe that the batch-size has an effect on the learning speed, stability during learning, and on the overall result. From the plots we can find that, small batches results in higher accuracy but the stability of using large batches is more than using small batches. Moreover, the time of training using high batch size is less than using a low batch size as shown in [Table 4](#).

From [Table 2](#), we can find that, the learning time of the proposed model using large batch-size is less than using small batch-size. However, the accuracy and the loss of the model using a small batch size are better than using large batch-size.

**Fig. 10.** Validation and training loss and accuracy for our model using min batch-size = 32.

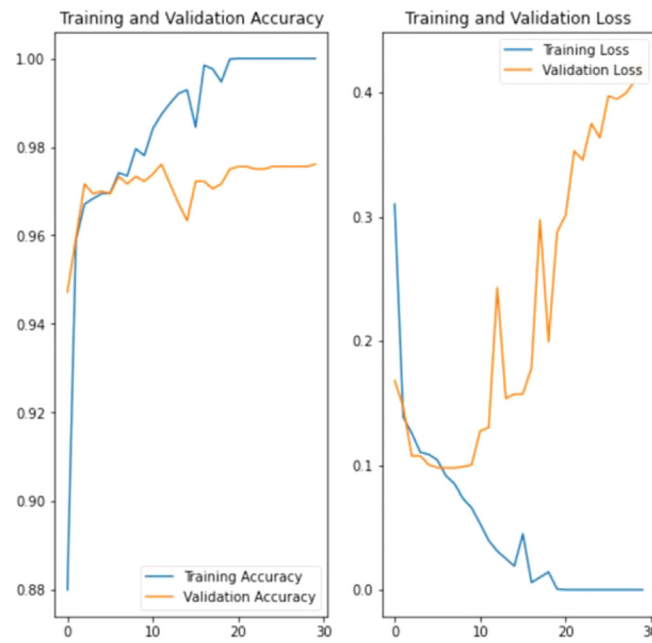


Fig. 11. Validation and training loss and accuracy for our model using min batch-size = 16.



Fig. 12. Validation and training loss and accuracy for our model using min batch-size = 8.

**Table 4**

The effect of using different batch-size on our model.

Batch-size	Accuracy	Loss	Learning time
32	0.9783	0.2013	450 sec
16	0.9765	0.1992	578 sec
8	0.9783	0.1233	900 sec
4	0.9881	0.1185	1200 sec

### 5.2. Problem with overfitting

Overfitting is caused by when large model training on a small dataset. This results in poor performance when evaluated the model on new datasets. Dropout is a regularization technique that trains in parallel large number of models with different architectures to avoid the overfitting. Dropout can implement in any layers of the model; in our case we add dropout layer before the dense layers. In addition to show the effect of dropout on our model, we changed the hyperparameter of the dropout and observe the results. Figs. 13 and 14 show the validation and training losses and accuracies of the proposed model in case of using different dropout probabilities (in our case we worked with 0.3 and 0.5).

From Figs. 13 and 14 we can find that, using the drop out decrease the accuracy but makes the system more robust and avoids any overfitting. However, the proposed model is already fit with the data without using any regularization techniques and achieved better accuracy. Moreover, the number of parameters of the model using drop out are larger than the number of parameters without using this technique. We obtained validation accuracies of 97.33 % and 96.50 % when using drop out with probability of 0.3 and 0.5, respectively.

### 5.3. Robustness of the system

In this case, we consider noisy versions of the input data by adding Gaussian noise on the input data. Fig. 15 shows the effect of Gaussian noise on some examples of the input data.

In addition, we computed the performance of the model using 5-fold and 10-fold cross validation as shown in Tables 5 and 6.

From the previous Tables, we can observe that the noise affected on the results of the model using the 5-fold strategy which decrease the accuracy from 99.99 % to 95.33 %. However, this result is acceptable compared with other previous models. When using 10-fold strategy, the accuracy almost the same with using the signals without noise where the difference is only 0.32 %. We can conclude that, the proposed model is robust against the noisy signals and achieved high accuracies compared with other previous models.

### 5.4. Comparison with other previous methods

COVID-19 detection at the early stages of disease appearance using easy and cheap ways is the key requirement for prudent application of control measures for this virus. Therefore, the main goal of this study is to propose a new method for the detection of COVID-19 using an easy and cheap technique. Many approaches are used to detect COVID-19. The most common approach is the detection of the virus from CT images or from MRI scans. However, this method needs laboratory analysis and technical knowledge, which is expensive and always unavailable. Besides this conventional technique, artificial intelligence has been used to detect COVID-19 recently. However, these methods are complex and still suffer from time and cost



Fig. 13. Validation and training loss and accuracy for our model using drop out with probability of 0.3.



Fig. 14. Validation and training loss and accuracy for our model using drop out with probability of 0.5.

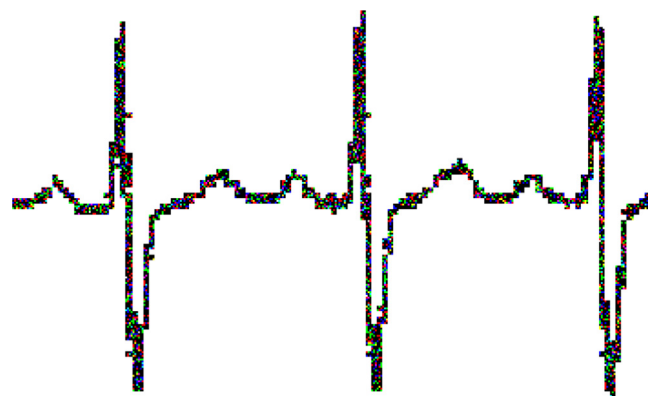


Fig. 15. The effect of gaussian noise on input ecg data.

**Table 5**

The results of our model using 5-fold cross validation on noisy data.

Folds	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)	Elapsed time (second)
1	94.66	94.66	94.66	94.66	28.847555637359
2	95.33	95.33	95.33	95.33	23.906558275222
3	88.66	88.66	88.66	88.66	24.032120227813
4	94.33	94.33	94.33	94.33	24.101620197296
5	94.99	94.99	94.99	94.99	23.969123601913

Avg Accuracy = 93.59 %, Best Accuracy = 95.33 %, Standard deviation = 2.78320.

complexity. Therefore, researchers developed a method based on ECG for COVID-19 detection (discussed in [Section 2](#)). To the best of our knowledge, very few studies explored the usage of ECG for COVID-19 detection. The comparison of our model (ECG-COVID) with these previous models using a 5-fold cross-validation technique on the same dataset is shown in [Table 7](#) and using a 10-fold validation technique is shown in [Table 8](#).

From [Tables 7 and 8](#), we can observe that the proposed model is more robust and efficient than other previous models with low cost and time. We can also find that most of the methods used augmentation techniques to increase the size of

**Table 6**

The results of our model using 10-fold cross validation on noisy data.

Folds	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)	Elapsed time (second)
1	96.66	96.66	96.66	96.66	30.902856826782
2	94.33	94.33	94.33	94.33	28.445235729217
3	92	92	92	92	28.443077087402
4	99.66	99.66	99.66	99.66	28.647143363952
5	88.99	88.99	88.99	88.99	29.022911071777
6	90.72	90.72	90.72	90.72	28.909217357635
7	94.33	94.33	94.33	94.33	28.479419231414
8	96.66	96.66	96.66	96.66	28.323496818542
9	94.49	94.49	94.49	94.49	28.478519916534
10	94.99	94.99	94.99	94.99	28.632184505462

Avg Accuracy = 94.28%; Best Accuracy = 99.66%; Standard deviation = 3.10344.

**Table 7**

Comparison between ECG-COVID and other previous method on the same dataset using 5-fold.

Authors/year	Approaches	Performance
Rahman <i>et al.</i> [9] 2022	Preprocessing and Augmentation Feature extraction and classification: deep learning pre-trained CNN models	The best accuracy = 99.1 % The best sensitivity = 0.991 The best precision = 0.991
Ozdemir <i>et al.</i> [10] 2021	Pre processing and segmentation Feature extraction: GLCM and Hexaxial Classification: CNN	The best accuracy = 93.60 % The best sensitivity = 0.960 The best precision = 0.916
Proposed 2022	Preprocessing, feature extraction and classification: the proposed ECG-COVID model	The best accuracy = 99.99 % The best sensitivity = 0.999 The best precision = 0.999

**Table 8**

Comparison between ECG-COVID and other previous method on the same dataset using 10-fold.

Authors/year	Approaches	Performance
Attallah [8] 2022	Preprocessing and Augmentation Feature extraction: pre-trained models + DWT Feature selection: entropy Classification: LDA, SVM, and RF classifiers	The best accuracy = 98.80 % The best sensitivity = 0.988 The best precision = 0.988
Emrah [31] 2022	Data augmentation Feature extraction and classification: CNN	The best accuracy = 98.57 % The best sensitivity = 0.992 The best precision = 0.977
Attallah [32] 2022	Preprocessing and Augmentation Feature extraction: pre-trained models Classification: ensemble classifier	The best accuracy = 98.20 % The best sensitivity = 0.968 The best precision = 0.996
Proposed 2022	Preprocessing, feature extraction and classification: the proposed ECG-COVID model	The best accuracy = 99.98 % The best sensitivity = 0.998 The best precision = 0.998

the data to obtain high accuracy. Our method is working on small data without using any augmentation techniques and also achieves high accuracy than all other methods. In addition, these previous methods used pre-trained models, which have many limitations (discussed in Section 2). Finally, we can highlight the advantages of the proposed method as the following:

- The proposed ECG-COVID is end-to-end without using any additional stages, which reduces the time and cost complexity.
- The proposed model is simple, which is established with a small number of layers with small number of parameters and is easy to use.
- Our model obtained high accuracy with small datasets. In addition, the model is fitted with the data without using any regularization techniques to overcome the overfitting problem.
- The proposed method is robust against noisy signals with high accuracies compared with other previous models
- The ECG-COVID is a lightweight model, which can be used for Mobile applications.
- Finally, the proposed model is efficient and more robust than other previous deep models for the detection of COVID-19 from the ECG data.

We want to confirm that a new end-to-end deep method based on ECG called ECG-COVID has been confirmed for COVID-19 detection.



## 6. Conclusion

The main goal of this paper is to propose a new end-to-end deep method based on ECG for COVID-19 detection. In this study, several CNN models are established and tested on the dataset. We selected the efficient and most robust model among these models for the evaluation and the comparison with the recent studies. We worked on 1109 ECG images that were labelled as 250 COVID-19 ECG images and 859 normal ECG images. Our method achieved an overall accuracy of 98.81 %, overall precision of 0.9881, an overall sensitivity of 0.9881 and an overall F1-score of 0.9881. The results show that the proposed model is more robust than another the previous model. The proposed method can be used in the worst-case scenarios, (i.e., cases of overcrowding in intensive care rooms and hospitals reaching their maximum capacity). In these cases, doctors can prioritize who has a chance of survival and who does not; In this way, more lives can be saved through careful rationalization of the use of resources. In the future, we can extend our idea by integrating other types of methodologies that deal with signal detection such as remote photoplethysmography (rPPG) in infrared [36].

## CRedit authorship contribution statement

**Ahmed S. Sakr:** Methodology, Software, Validation, Writing – original draft. **Paweł Pławiak:** Supervision, Investigation, Writing – review & editing. **Ryszard Tadeusiewicz:** Supervision, Writing – review & editing. **Joanna Pławiak:** Investigation, Writing – review & editing. **Mohamed Sakr:** Software, Validation. **Mohamed Hammad:** Conceptualization, Methodology, Data curation, Writing – original draft, Software, Validation.

## Data availability

Data will be made available on request.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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