Research Square

Preprints are preliminary reports that have not undergone peer review. They should not be considered conclusive, used to inform clinical practice, or referenced by the media as validated information.

Coronavirus Disease (COVID-19) Detection using Deep Features Learning

Zainab A. Khalaf (zainab_ali2004@yahoo.com)
Basrah University https://orcid.org/0000-0002-8964-0113
Saad S. Hammadi
Basrah University
Alaa K. Mousa
Basrah University
Hanan M. Ali
Basrah University
Hanan R. Alnajar
Basrah University
Raghdan H. Mohsin
Basrah University

Research Article

Keywords: Coronavirus, COVID-19, Deep Learning, Classification, CT-Scan

Posted Date: August 19th, 2020

DOI: https://doi.org/10.21203/rs.3.rs-60331/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Coronavirus Disease (COVID-19) Detection using Deep Features Learning

Zainab A. Khalaf ✉[1], Saad S. Hammadi[2], Alaa K. Mousa[2], Hanan M. Ali[3], Hanan R. Alnajar[4] and Raghdan H. Mohsin[5]

[1]Department of Mathematics , College of Science , University of Basrah , Email: zainab_ali2004@yahoo.com
[2]College of Medicine, University of Basrah
[3]Department of Chemistry , College of Education for Pure Sciences , University of Basrah
[4]Department of Pathological Analysis , College of Science , University of Basrah
[5]Department of Animal Production , College of Agriculture , University of Basrah

I. Abstract

Coronavirus (COVID-19) pandemic detection considers a critical and challenging task for the doctors. The coronavirus disease spread so rapidly between people and infected roughly fourteen million people worldwide. For this reason, it is very much necessary to detect infected people with coronavirus and take the action to prevent of spread this virus. In this study, the COVID-19 classification methodology is adopted to detect the infected patient with coronavirus using CT images. The deep learning is applied to recognize the affected CT images of COVID-19 from others by employing the deep feature. This methodology can be beneficial for the medical practitioner to diagnosis the infected patient with coronavirus. The result is based on new data collections named BasrahDataset that included different CT scan video for Iraqi patients. The system gives promised results with 99% F1-score for detecting COVID-19.

Key Words : Coronavirus, COVID-19,CNN, Deep Learning, Classification, CT-Scan.

II. Introduction

In December 2019, a novel coronavirus called 2019- nCoV ("n" stands for a novel) is spread. This virus causes Severe Acute Respiratory (SARI) symptoms, including dyspnea, fever, asthenia as well as pneumonia among Chinese people (specifically in Wuhan). The first batch of Chinese patients infected roughly all associated with the seafood market in Wuhan that also trades wild animals. Then, contact transmission of 2019-nCoV was confirmed among humans, and the number of infected Chinese patients increased quickly not only in Wuhan but also in other major cities in China. Many actions have been taken by the Chinese government to avoid and control the pandemic of the virus, but the coronavirus spread rapidly outside china and moves in the world. Like any place in the world, many COVID-19 positive cases appeared in Iraq. Then, the number of individuals that contracted the virus increased sharply and continues to evolve rapidly. On 23 June, the positive cases reaching 34,502 patients with increase in the number of deaths significantly. Roughly 40% of these cases identified in Baghdad [1], [2], [3], [4].

The diagnosis of coronavirus (COVID-19) nowadays is a critical task for the medical practitioner, especially with an increased number of patients and a variety of symptoms. The test of COVID-19 (especially in Iraq) is currently a difficult task due to the unavailability of the diagnosis system in every city in Iraq, which is causing delays in disease detection. due to the limited of COVID-19 testing kits that are available, so another diagnosis measures are needed to rely on. As a result, some prevention schema to avoid virus spread can be taken when identifying infected people. Since COVID-19 attacks the epithelial cells that line our respiratory tract, we can use CT Scan images to analyze the health of a patient's lungs. The CT images are used frequently by the medical practitioner to diagnose lung inflammation, pneumonia, abscesses, and/or enlarged lymph nodes. So, all hospitals almost having CT imaging machines that can be used to test for COVID-19 instead of the dedicated test kits. the main problem of using CT images is that the analysis of CT images requires a radiology expert and it takes a long time causing time-consuming, which is precious for the sick people. Therefore, it is necessary to develop an automatic system capable of analyzing the CT images to save the valuable time of medical professionals.

Deep VGG-16 is used that consider as a specific subarea of machine learning. VGG-16 is a multilayers convolution neural network (CNN) by using tens/hundreds of representations of successive layers in its architecture. The deep layer is the function of a data transformation that performs the data transformation which goes through that layer. These transformations are parametrized using a different set of weights and biases in order to identify the transformation behavior at each layer. VGG-16 is commonly utilized in many deep learning image classification problems due to it is easy to implement and handle a large number of a dataset that may be belonging to a larger number of classes. in this paper, VGG-16 is used to classify COVID-19 CT images either it's positive or negative cases for a dataset that collected for Iraqi patients.

The remaining sections of this paper are structured as the following: Section (III) is a review of the related works. While the section (IV) discusses the classification system. In section (V), the proposed system is presented. Materials and Methods will be shown in section (VI). The experiments and the result will be discussed in section (VII). Section (VIII) shows the discussion of the results. Finally, the conclusions are shown in section (IX).

III. Related Works

Researchers work hard to detect the COVID-19 virus automatically in order to help doctors to control on the quickly spread the virus between people either by helping to identify coronavirus (COVID-1(9 at an early stage and make decisions in clinical practice the or by reducing time consuming of doctors efforts and the limited used tools for detection.

Li et al. [5] used CT chest images to examine the relationship between the manifestations of CT imaging and clinical categorization of COVID-19. They conducted a retrospective single-center study on 78 patients (38 males and 40 females) with COVID-19 from 18 January 2020 to 7 February 2020 in Zhuhai city, China that divided the patients into three types based on Chinese guideline. The first type is mild included patients with negative CT image findings and minimal symptoms. the second type is common, and the third one is severe-critical included patients with different extent of clinical manifestations and positive CT image findings. They used different scores to CT visual quantitative estimation that based on summing up the acute lung inflammatory lesions comprising each lobe. The TSS (Total severity score) was compared with the clinical classification. The cutoff point of TCC is 7.5 that yielded 82.6% sensitivity and 100% specificity. They conclude that the ratio of COVID-19 patients of mild-type was comparatively high; CT image was not appropriate for an independent screening tool. The visual quantitative analysis of CT image has high consistency and consequently can reflect the clinical categorization of COVID-19.

Narin et al. [6] used three different CNN based models (ResNet50, InceptionV3 and Inception- ResNetV2) to detection the infected patient with coronavirus pneumonia utilized chest X-ray radiographs. They used ResNet50 to pre-trained the model. The classification accuracies were 98%, 97% and 87% for ResNet50, InceptionV3 and Inception-ResNetV2 respectively. The experimental result based on using 100 chest X-ray images dataset (50 images of normal cases, and 50 COVID-19 patients). The authors concluded that using the automatic detection of COVID-19 can help doctors to expose coronavirus at an early stage, and consequently the appropriate decisions can be taken in clinical practice based on the high performance of the classification model.

Barstugan et al. [7] used different CT tools to extract the coronavirus image set. These images dataset was collected manually included 150 CT abdominal images that belong to 53 infected cases, from the Societa Italiana di Radiologia Medica e Interventistica (6). to extract images features, five feature extraction approaches (Grey Level Co-occurrence Matrix, Grey Level Size Zone Matrix, Grey Level Run Length Matrix, Local Directional Pattern, and Discrete Wavelet Transform) utilized to exclude the irrelevant feature set. The classification accuracy achieved 99.68%.

Sethy et al. [8] used deep learning for detection of coronavirus infected patient utilized X-ray images. the features extracted from the deep feature of nine pre-trained CNN model and passed to SVM classifier model individually. Two datasets utilized in this study, the first dataset included 25 positive cases and 25 negative cases that collected from the GitHub repository with shared by Dr. Joseph Cohen [9] and Kaggle repository [10]. While the second dataset included 266 (133 positive cases and 133 negative cases) that collected from the Open-i repository [11]. The classifier system achieved 95.52%, 95.38% of F-Score, and accuracy respectively, for detecting COVID-19 disease (ignoring ARDS, MERS, and SARS).

Song et al. [12] collected 275 CT scan images from two hospitals in China distributed to 88 positive COVID-19 cases, 101 images for patients that infected with bacteria pneumonia, and 86 images for healthy persons. They used four Deep Learning Model (VGG-16, DRENet, ResNet, and DRE-Net) for Pneumonia Classification. The best f-score result was 0.87% in the test set.

IV. VGG-16 Neural Network

Simonyan et al. [13] proposed VGG-16 architecture as a convolutional neural net (CNN) model. They used this model to win ILSVR (The ImageNet Large Scale Visual Recognition Challenge (ILSVRC)) competition in 2014. VGG-16 consists of sixteen layer network and considered one of the best vision model frameworks to date. VGG-16 model yielded 92.7% top-5 test accuracy in ImageNet dataset that included over fourteen million images distributed into 1000 classes belongs to. to train VGG-16, many weeks were required. As shown in Fig. 1, the VGG-16 structure of the layers can be summarized as follows:

First and Second Layers: The input image is $224 \times 224 \times 3$ passed through a stack of first and second convolutional layers with 64 feature maps or 3×3 filters and stride 14 for same pooling. The dimensions of the images will be changed to $224 \times 224 \times 64$. Then, the maximum pooling layer or layer of sub-sampling will be applied in the VGG-16 with a filter size 3×3 and stride 2. The dimensions of the resulting image will be minimized to $112 \times 112 \times 64$.

Third and Fourth Layer: After that, Two convolutional layers are applied with 128 feature maps having filtering size 3×3 with a stride of 1. Next, maxpooling layer with filter size 3×3 with a stride of 2 is implemented, which consequently reduces

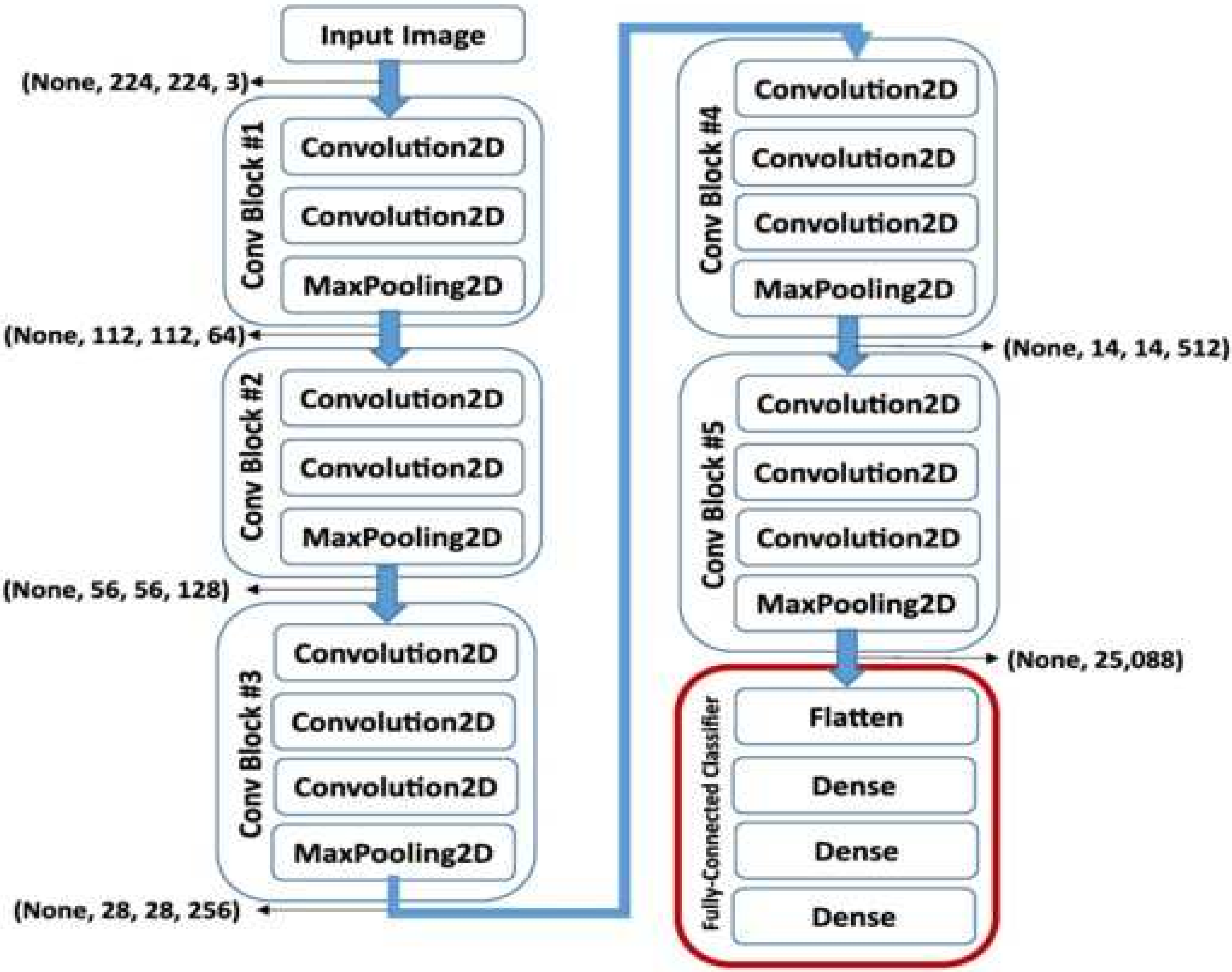

Figure 1: VGG-16 Neural Network Architecture

the dimension of the resulting image to $56 \times 56 \times 128$.
Fifth and Sixth Layers: These two layers are convolutional layers having filter size 3×3 with a stride of one. Both layers utilized 256 feature maps. The next layer of these convolutional layers is the layer of maximum pooling having filter size 3×3 with a stride of two and 256 feature maps.
Seventh to Twelveth Layer: These convolutional layers that followed by a maximum pooling layer having 512 filters of size 3×3 with a stride of one. The final dimension will be decreased to $7 \times 7 \times 512$.
Thirteenth Layer: The Fully-Connected (FC) layers are used to flatten the convolutional layer output with 25088 feature maps each of size 1×1.
Fourteenth and Fifteenth Layers: These layers consist of two fully connected layers with 4096 units.
Output Layer: The final layer is the softmax output layer with 1000 classes.

V. The Proposed System

Image classification is the process of automatically assigning a class label to the new images based on pre-defined patterns created from labeled data. The classification system divides the data into training and testing phases, with the training phase a parameters are obtains and used in the testing phase to predict the label to the new images. The adopted classification system consists of four main phases (Fig. 2): pre-processing stage, deep CNN feature extraction phase, classification phase, and evaluation phase. The processing is an important stage to prepare the images for the next phase. Next, the feature extraction is applied to extract the features and excluding the unimportant features using deep learning filtering. Then, the extracted features will be passed to the classifiers to find the best results. Finally, the evaluation is applied to compute the classifier performance. In the following subsections, these phases are explained.

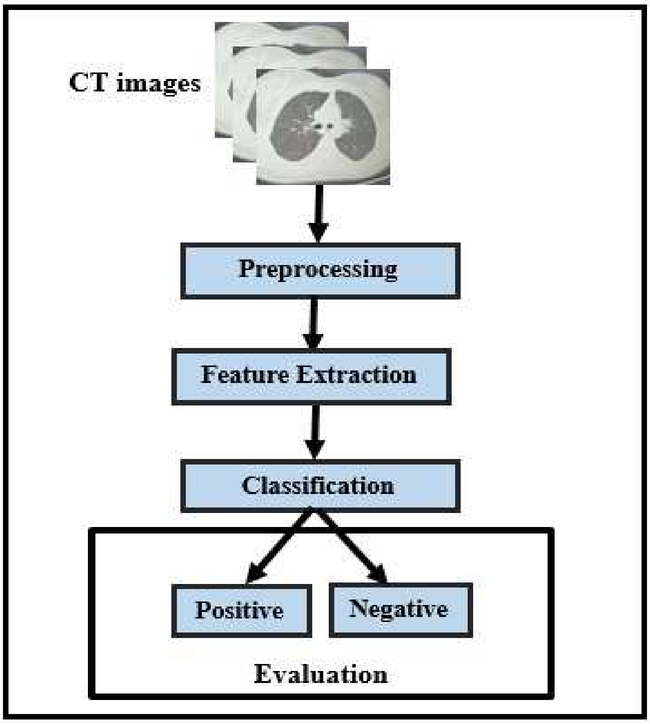

Figure 2: The Adopted Classifiaction System

A. Preprocessing Phase

The preprocessing is an important stage to prepare the image for the next step. The pre-processing is a set of processes that applied to the image to exclude the noise and extract the region of interest (ROI). In the first step, the CT image is transformed into the grayscale and resizes the images. All the images in the dataset will be passed as input to the VGG-16 neural networks model with the same size. So, all images need to be resized into a fixed size with less shrinking to avoid the classification accuracy degradation due to deformations. Besides, the amount of the required memory and computational operations for image processing also will be reduced. [14] [15] .

B. Deep CNN Features Extraction

Deep CNN framework composed of different layers used as a feature extractor. Earlier CNN layers have more low-level features compared with the highest level (convolution layer or pooling layer). The CNN hidden layers consist of one or more convolutional layers each follow up by a pooling layer in sequence manner and follow up by one or more fully connected (FC) layers. The CNN convolutional layers are used to extract the relevant features, while the last FC layer used as the classifier. The convolutional layers comprised form two different layers: the filter bank layer as well as the non-linearity layer. The features are mapped as matrix and passed as input to the convolutional layers. The matrix dimensions are $W \times H \times 3$, where W and H are the widths, and the height respectively, and 3 (three-color channeled RGB image) is the number of feature maps. The layers of the filter bank include multiple trainable kernels associated with each feature map. each kernel capable of identifies a specific feature from the input matrix at every location. on the other hand, the non-linearity layer implements on the output a nonlinear activation function from the filter bank layer. After that, the pooling layers are applied to sub-sampling for each feature map in order to decrease the map resolution. Then, the output of the convolutional layers is passed to FC layers. During FC layers, the final decisions based on different weighted combinations of the inputs are making to determine the class that the image belongs to [15].

C. Classification Phase

First, the Support Vector Machine (SVM) classifier is used to train the images. Then, the learned classifier is applied to the test images by fed the features obtained from the previous layers to the SVM classifier to identify the COVID-19 either positive or negative.

D. Evaluation Phase

The performance of the classification can be evaluated by using Precision, Recall, and F1-score [19]. The classification system performance was measured with the F1-score and the Accuracy [7]. That calculated by the formulas:

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

$$F - measurey = \frac{(2 \times Recall \times Precision)}{(Recall + Precision)} \tag{2}$$

Where TP, FP, TN, FN, Precision and Recall calculated as following:
True positive (TP): the number of correctly recognized class cases
False positive (FP): the number of correctly recognized cases that do not belong to the class
True negative (TN): cases that were incorrectly assigned to the class
False negative (FN): cases that were not recognized as class cases.

Precision: is the number of correctly classified positive cases divided by the number of cases labeled by the system as positive.

$$Precision = \frac{TP}{(TP + FP)} \tag{3}$$

Recall: is the number of correctly classified positive cases divided by the number of positive cases in the data

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

VI. MATERIALS AND METHODS

The data used in this current study collected from Al-Sadr educational hospital in Basrah City of Iraq. This data was collected by specialed in Infectious diseases from the period April to June 2020 included the Chest X-ray (CXT), and Computed Tomography (CT) Scan images. This data includes 50 cases distributed into 30 males and 20 females with two classes (positive and negative COVID-19 cases). The age of the patients ranged between 18 and 65. The total images are roughly 1420 (1181 positive cases, and 242 negative cases). These data confirmed by clinical picture plus to CT scan nasal of oral swab Polymerase Chain Reaction Test (PCR). The use of this data in the current study is based on the official approval document issued by the Al-Sadr educational hospital.

The automatic detection system is built based on the above expert experience by divide the data into two datasets. The first one used to learning the extracted deep feature to build the classifier model using VGG-16 and another one is to identify the COVID-19 infected patient automatically by using this built model. Keras package in python language (version 3.7.4 64-bit) used to design VGG Model.

VII. EXPERIMENTAL RESULTS

The convolutional neural network (CNN) architecture is executed with many layers such as convolutional, ReLu, pooling. The Relu activation function is used in hidden layers and Softmax is used in the output layer. Also, Average and fully connected layers are used. Further layers are used like dropout that added to the network to improve the classifier performance during the training phase. This layer activated only in the training phase to drops a certain number of neurons randomly during forward pass. the non-dropped neurons are updated during the backward pass. The main purpose of dropout is to bring the regularization to learn the model with a robust feature and avoids overfitting during the training phase.

A. Databases

Many video data collections used in the current study that collected manually for Iraqi patients in Basrah City called (BasrahDataset). BasrahDataset which contains 50 cases that annotation from up to four experienced thoracic radiologists. This dataset includes 30 males and 20 females distributed into two classes (positive case and negative). The age of the patients ranged between 18 and 65. First, the videos segmented to images at every 10 frames. The total images are roughly 1420 that divided into two groups: training and testing. Training data comprised approximately 820 images with 694 images confirmed COVID-19 cases. While, 124 images are negative case. On the other hand, 487, and 118 positive and negative cases respectively used for testing (605 images in total). Fig. 3 shows an example of BasrahDataset CT images.

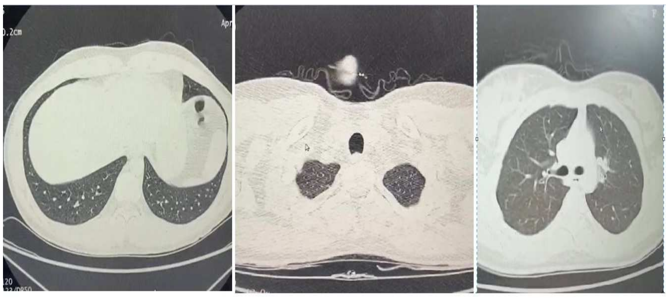

Figure 3: An Example of CT Images

B. The Classifiers Performance

This section describes the experimental performance of the conventional approaches that frequently implemented in image classification. In deep CNNs, different layers correspond to a hierarchy of features; earlier layers represent more low-level features. Thus, the CNN relevant features are extracted at the highest level (either last convolution or pooling layer) to encode manifestation relationships. In current work, the VGG-16 CNN classifier model with the AveragePooling layer that applied in the CNN framework is utilized as a black box deep CNN features extractor. From the first fully CNN connected layer, The high-level features were extracted and are of dimension 4096. The deep VGG-16 CNN model is trained on BasrahDataset. The AveragePooling layer of the CNN framework is considered as surveillance operation that used to dramatically enhance the computation time by executing only one feed-forward evaluation for the multiple proposals operations that come from the previous stage. In recap, the input images size is set to $224 \times 224 \times 3$. The VGG-16 CNN model is used to train on the BasrahDataset to extract the deep features. The softmax classifier is used in the output layer for the COVID-19 classification. The classifier system produced 99% classification accuracies and F-score. Besides, the adopted classification system achieved better results compared to the related works. Table (1) shows other researchers' works using different classification systems and datasets. The advantage of our work is using a large number of dataset with high accuracy.

VIII. DISCUSSIONS

The input CT images are passed into the CNN detection pipelines that started with deep feature extraction and ended with making decisions. The detection performance in the current study is evaluated utilized the VGG-16 pipeline CNN based on the loss-accuracy curves to obtain the best class. The BasrahDataset is used for evaluation. The total images are roughly 1420 that divided into two groups: training, validation, and testing. Roughly 820 CT images used for training and validation (80% images for training and 20% for validation). Then, 605 CT images are used to evaluate the pre-trained model. Fig. 4 shows the experimental results with the best accuracy and loss. The right prediction rate of a dataset of train or validation images is represented by a point in the accuracy curve. We can notice that the accuracy of the training dataset to around 100% after 10 epochs as well as the validation set accuracy. The test accuracy of BasrahDataset testing images is 99%.

Reference	Classifier	Type of Data	Amount of Data	Classifier Performance
Li et al. [5]	Statistical analysis	CT chest images	78 patients	82.6% Sensitivity,100% Specificity
Narin et al.[6]	CNN	Chest X-ray images	100 images	98% Accuracy
Barstugan et al. [7]	SVM	CT chest images	150 images	99% accuracy
Sethy et al. [8]	CNN model	Chest X-ray images	316 images	95.52% F-score, 95.38% Accuracy
Song et al. [12]	VGG-16	CT chest images	275 images	84% F-score and Accuracy
Current Study	VGG-16	CT chest images	1425 images	99% F-score and Accuracy

Table 1: Comparisons with Related Works

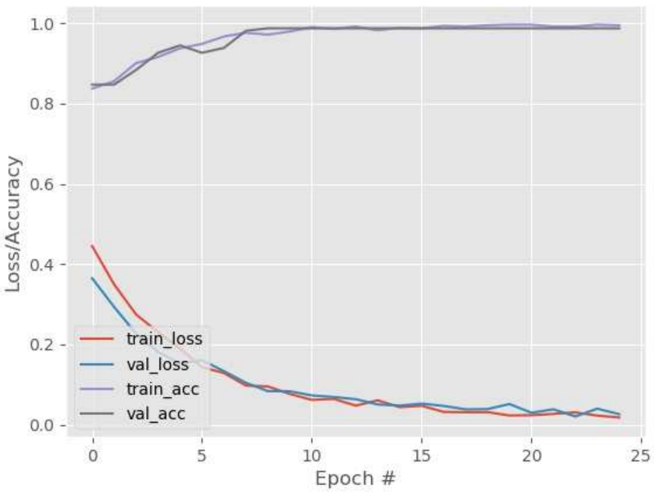

Figure 4: Loss and accuracy on BasrahDataset

IX. Conclusion

In this paper, a deep classification learning is adopted to identify COVID-19 CT images. These images collected for Iraqi patients in Basrah city consisted of 1425 CT images for positive and negative COVID-19 cases. The classification model extracts the features from the pre-trained dataset. Then, the SVM classifier used to recognize the coronavirus cases. The classification system achieved relatively high performance on BasrahDataset CT images. Besides that, the results also compared with some related works. As future works, we can be classified the coronavirus based on the degree of infected.

References

[1] Y. X. Lim, Y. L. Ng, J. P. Tam, and D. X. Liu, "Human coronaviruses: a review of virus–host interactions," *Diseases*, vol. 4, no. 3, p. 26, 2016.

[2] A. R. Sahin, A. Erdogan, P. M. Agaoglu, Y. Dineri, A. Y. Cakirci, M. E. Senel, R. A. Okyay, and A. M. Tasdogan, "2019 novel coronavirus (covid-19) outbreak: a review of the current literature," *EJMO*, vol. 4, no. 1, pp. 1–7, 2020.

[3] X. Liu and X.-J. Wang, "Potential inhibitors against 2019-ncov coronavirus m protease from clinically approved medicines," *Journal of Genetics and Genomics*, vol. 47, no. 2, p. 119, 2020.

[4] T. Singhal, "A review of coronavirus disease-2019 (covid-19)," *The Indian Journal of Pediatrics*, pp. 1–6, 2020.

[5] K. Li, Y. Fang, W. Li, C. Pan, P. Qin, Y. Zhong, X. Liu, M. Huang, Y. Liao, and S. Li, "Ct image visual quantitative evaluation and clinical classification of coronavirus disease (covid-19)," *European radiology*, pp. 1–10, 2020.

[6] A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks," *arXiv preprint arXiv:2003.10849*, 2020.

[7] M. Barstugan, U. Ozkaya, and S. Ozturk, "Coronavirus (covid-19) classification using ct images by machine learning methods," *arXiv preprint arXiv:2003.09424*, 2020.

[8] P. K. Sethy and S. K. Behera, "Detection of coronavirus disease (covid-19) based on deep features," *Preprints*, vol. 2020030300, p. 2020, 2020.

[9] "GitHub repository ," www.github.com/, [Online; accessed 16-March-2020].

[10] "Kaggle repository ," www.kaggle.com/, [Online; accessed 16-March-2020].

[11] "Kaggle repository ," https://openi.nlm.nih.gov/, [Online; accessed 16-March-2020].

[12] Y. Song, S. Zheng, L. Li, X. Zhang, X. Zhang, Z. Huang, J. Chen, H. Zhao, Y. Jie, R. Wang *et al.*, "Deep learning enables accurate diagnosis of novel coronavirus (covid-19) with ct images," *medRxiv*, 2020.

[13] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition, september 2014," *URL http://arxiv.org/abs/1409.1556*, 2016.

[14] D. Zhao, D. Zhu, J. Lu, Y. Luo, and G. Zhang, "Synthetic medical images using f&bgan for improved lung nodules classification by multi-scale vgg16," *Symmetry*, vol. 10, no. 10, p. 519, 2018.

[15] Y. H. Liu, "Feature extraction and image recognition with convolutional neural networks," in *Journal of Physics: Conference Series*, vol. 1087, no. 6, 2018, p. 062032.

Competing interests: We declare that there are no competing interests.

Figures

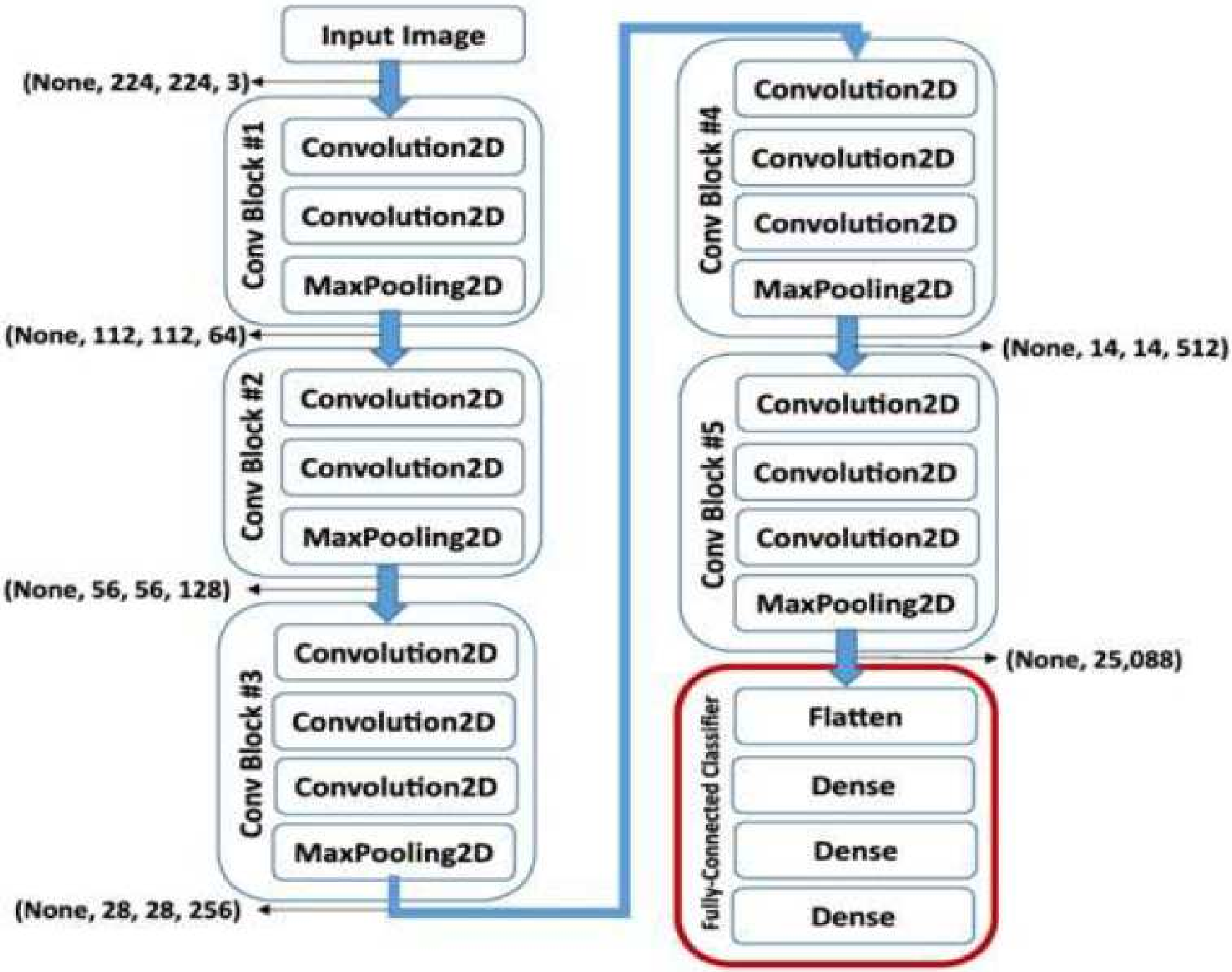

Figure 1

VGG-16 Neural Network Architecture

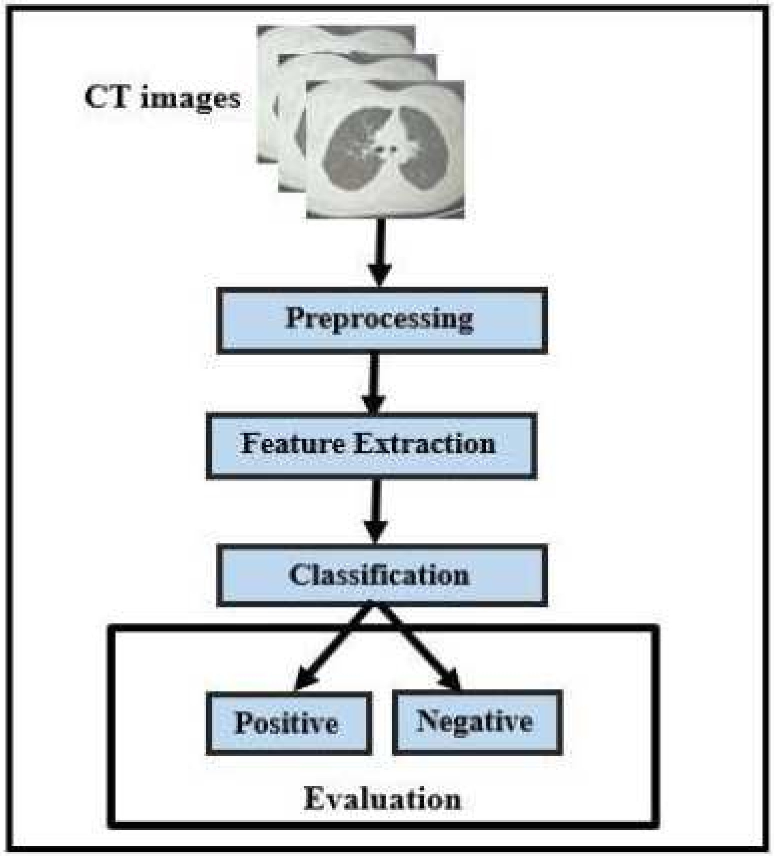

Figure 2

The adopted classification system

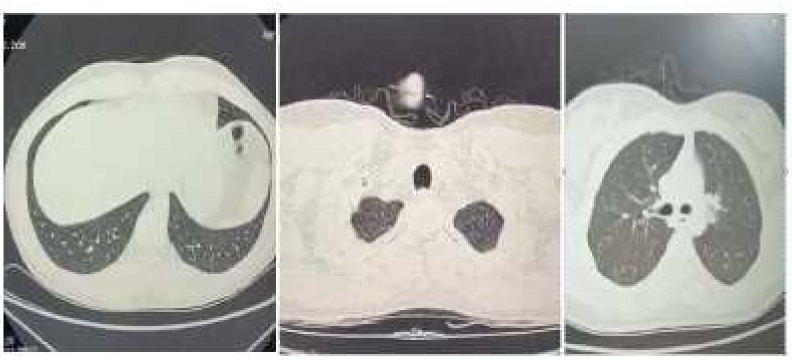

Figure 3

An example of CT images

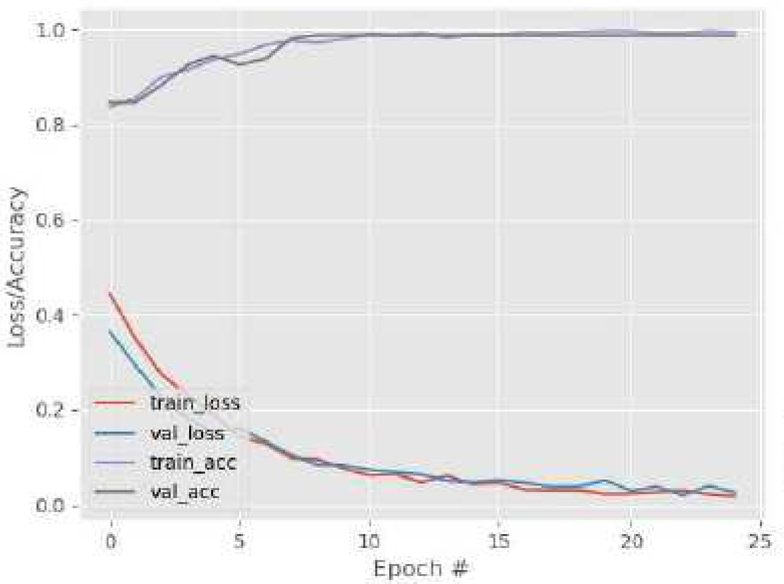

Figure 4

Loss and accuracy on BasrahDataset