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The diagnosis of COVID-19 in CT images using hybrid machine learning approaches (CNN & SVM)

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ABSTRACT

The new coronavirus disease (2019) has spread quickly as an acute respiratory distress syndrome (ARDS) among millions of individuals worldwide. Furthermore, the number of COVID-19 checking obtainable in hospitals is very limited as compared to the rising number of infections every day. As an outcome, an automatic detection system must be implemented as a quick diagnostic tool for preventing or reducing the spread of COVID-19 among humans. The present paper aims to propose an automated system by means of a hybrid Deep Learning ("convolutional neural network"(CNN)) and "support vector machine (SVM)" approach for identifying COVID-19 pneumonia-infected patients on the basis of chest computed tomography (746 CT images of "COVID-19" and "non-COVID-19"). The proposed system is composed of three phases. The first, pre-processing phase begins with converting CT images into greyscale level CT images of equal size (256×256). The "contrast limited adaptive histogram equalization" technology is adopted to enhance the intensity levels, and demonstrate the feature of lung tissue. It is also necessary to normalize the division of the image elements by 255 to make the values between 0 and 1, as this will speed up the processing process. The second phase, the CNN (SimpNet model), was applied as a deep feature extraction technique to identify CT samples. The SVM classifier and SoftMax function are employed in the third phase to classify COVID-19 pneumonia-infected patients. Specificity, Sensitivity, "F-score", Accuracy, and "area under curve" are used as criteria to estimate the efficiency of the classification. The results showed a high accuracy rate of COVID-19 classification which reached (98%) and (99.1%) for CNN-SoftMax and CNN-SVM classifier, respectively in the tested dataset (225 CT images).

Keywords: Classification, Convolutional Neural Networks (CNN), Computed Tomography (CT), Support Vector Machine (SVM), Coronavirus Detection.

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1. Introduction

"Covid-19" infection is a new virus strain first discovered in China, specifically in the Wuhan region in 2019. It is an acute infectious virus that really has harmed the health of millions of people worldwide by negatively impacting the respiratory system [1]. Covid-19 is highly infectious and must be quickly detected so that the affected individuals can be separated rapidly for preventing the pervasion of infections. The "Reverse Transcription - Polymerase Chain Reaction (RT-PCR)" is a fundamental measure for diagnosing cases of the Covid-19 disease, and it involves discovering RNA from sputum or a nasopharyngeal sample. The RT-PCR test has many limitations, including the fact that it requires a very long time to obtain results. The supply of materials in hospitals is still minimal, and it has an approximately low positive discovery rate in the primary stages, as stated by World Health Organization. With these limitations, individuals who are diagnosed with Covid-19 are in hazard, and the contagious nature of the new disease will cause viral infections in many healthy individuals. For this purpose, chest CT scans have been adopted as an alternative means for diagnosing Covid-19 infection. Radiographic specimens on CT chest images tend to show more sensitive and specific observations regarding the discovery of Covid -19. In addition, much information can be extracted from the CT scan images [2]. COVID-19 confirmation is challenging for radiologists through visual scanning, as they have to look for ground-glass opacity (GGO) in the lungs. As a result, the use of machine learning (ML) is necessary for introducing an automatic identification system as a rapid substitute diagnosis alternative, so as to prevent COVID-19 from spreading to among individuals. Machine learning applications in medicine have resulted in several studies which attempt to recognize multiple diseases (including brain tumors) from magnetic resonance (MR) pictures, and pulmonary diseases (like pneumonia) using X-Ray and CT scans images. Deep learning techniques CNN and SVM have resulted into a shift in expectations for many artificial intelligent applications in data processing, as it reached human-level accuracy in different tasks such as "medical image analysis" [3]. In recent years, AI has witnessed a significant and rapid growth, with"deep neural network" as the first instrument for solving different problems like speech recognition, object detection, and image classification. CNNs with the data augmentation technique showed good image classification results. Multiple studies have demonstrated the strength and reliability of these techniques for image segmentation. The architectures of CNN for medical imaging also have been deployed with perfect performance for both image recognition and image segmentation.

2. Related works

In the related works, numerous projects have been submitted in relation to the detection of Covid-19 cases. These studies are mainly related to extracting lung tissue characteristics through CT or X-ray images. As for the techniques that have been used to extract the characteristics, most of the researchers used CNN models such as vggnet, resnets, alexnet, googlenet, densnet and simpnet [4]. The majority of studies have deployed ML algorithms to diagnose COVID-19 infections. In [5] the authors proposed built an open-source data set from CT images of Covid-19 patients, which consists of 746 CT scans image (349 of "COVID CT images", and 397 of "non-COVID CT images"). In this data set, some information regarding the patients was presented, such as the age and gender of the patients, and other specific characteristic manifestations of Covid19. They also used this dataset to develop disease diagnostic techniques based on self-supervise learning and multi-tasking learning, achieving an "Area under Curve" of 98%, an accuracy rate of 89%, and an F1-measure of 90%. In [6] the authors deployed five various deep CNN-based models (resnet50, vggnet19, googlenet, vggnet16, and alexnet) to diagnose Covid pneumonia in patients. This work made use of data augmenting techniques and "Conditional Generative Adversarial Nets" (CGAN) through a deep transfer learning system for diagnosing COVID-19 in computed tomography images. The results obtained the most satisfactory classification efficiency using the resnet50 model with a testing specificity of 87.62%, a sensitivity of 77.66%, and an accuracy of 82.91%. Deep learning technology was used by [7] to distinguish between COVID-19 CT images and good health CT images. The obtained results include an "F1 score" of 0.89, an accuracy of 0.89, and an “Area under Curve" of 0.89. The proposed deep learning architecture is was efficient in detecting COVID-19 in a relatively short period of time. This approach employs cyclic learning rates, constant learning rates, and decreasing learning rates strategies (decrease on the plateau) to ensure that the model’s performance remains developing. In [8] the authors introduced a sequential CNN based model for identifying COVID-19 by means of the analysis of CT scan images. The method can identify the disease efficiently, as it obtained comparatively sufficient results for each of the specificity, sensitivity, "accuracy", "precision", and "f1 score" rates of this model, being 89%, 94%, 92%, 93%, and 94%, respectively. Different deep CNN-based techniques were investigated by [9] for identifying the existence of COVID from computed tomography (CT) scans. A system based on decision fusion is also presented, whereby predictions of several individual technologies are combined (densenet201, densenet121, inceptionv3, resnet50, and VGG16) through the majority voting method for producing final predictions. The results indicated that this method has the best classification efficiency in the decision fusion-based approach, with a testing accuracy of 86%. In [10] the authors proposed introduced an automated COVID19 detection system using the novel deep CNN structure on the CT dataset. They also applied data augmentation and the laplace filter to the CT images to increase the number of training data, as well as to significantly increase the CNN performance in COVID-19 diagnosis. The highest accuracy achieved was 92%.

3. Material and methods

The proposed system is composed of three stages. The first phase is the pre-processing, which begins by converting CT images into grey level CT images of equal size (256×256). The CLAHE technology was applied to enhance contrast, demonstrate the feature of lung tissue, and normalize the division of the image elements by 255 to make the values between 0 and 1, so as to speed up the processing procedure. The second phase, the CNN (simpnet model) technique, was applied as a deep feature extraction technique to identify CT samples as being either Covid or Non-Covid. In the third phase, SVM and softmax are deployed to classify Covid pneumonia-infected patients. The proposed approach is demonstrated in Figure 1.

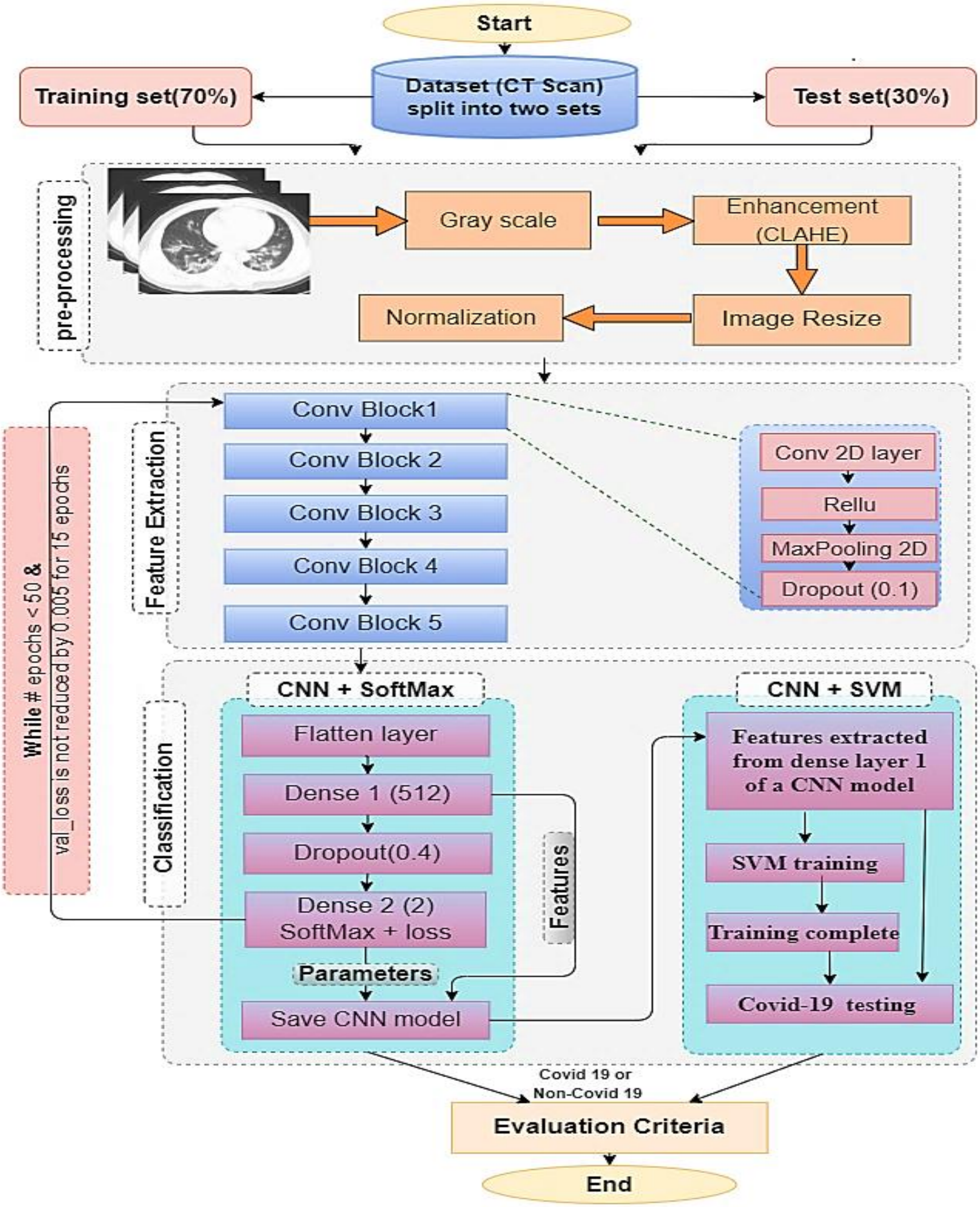


Figure 1. The proposed system flowchart

3.1. Pre-processing phase

Operations of pre-processing are a series of fundamental steps in the Covid-19 classification system to initialize data for the next stage (the feature extraction stage). It also focuses on disease-specific features to increase the model's accuracy. It consists of four steps: converting CT images to grayscale images, resizing CT images, enhancing CT images using CLAHE technology, and normalization.

3.1.1. Converting CT color scan to CT grayscale scan

The benefits of transforming a CT Color scan to a CT grayscale scan (monochrome) domain are related to the decreasing of data, since the grayscale field contains only one channel. In contrast, color images contain three channels (RGB) which contribute to speeding up the programs' execution.

3.1.2. Resizing CT images

All CT images are loaded to be scaled at a fixed size of (256×256) to efficiently suit the processing in deep learning systems. This step decreases the computational cost, as resizing the CT images to a (256×256) pixel scale improves the processing efficiency.

3.1.3. CT images enhancement (CLAHE)

In this step, the CT scanning image pre-processing is performed using the CLAHE technique. This is a contrast enhancement approach that efficiently raises the image's contrast, eliminates noise and blurring, sharpens the features, and shows the details of the image (such as edge and boundary detection) without changing the natural structure of the CT image. The main idea of this method is to first divide the input image into small parts of equal and non-overlapping sizes, which are called tiles. Then, the histogram is computed for each part because this method does not use the global histogram and depends on the local histogram. Next, this method clips the histogram at specified values to overcome the noise over-amplification problem and regularly distributes it to other tiles before calculating the cumulative distribution function. After that, the cumulative histogram is computed to create the equalization. The CLAHE technique applies two parameters; the clip limit (CL), which is a numerical value specifying noise amplification, and the number of tiles (NT), which is a numerical value that specifies the number of non-overlapping sub-regions.

3.1.4. Normalization

Normalization is a method used in image processing whereby the range of pixel intensity values that may be seen is changed. CT images with poor contrast because of glare are one example of this phenomenon. The terms "normalization" and "contrast stretching" are often used interchangeably, as is the phrase "histogram stretching". Dynamic range expansion is the term used to refer to this technique in more common area of data treatment, which includes digital signal processing. For various applications, the goal of dynamic range expansion is always a picture or another kind of data towards a more familiar or typical range, hence the word normalization. When dealing with a collection of data, signals, or images, the aim is often to preserve the dynamic range of the collection.

3.2. Feature extraction phase

CNN is an example of the types of "deep neural networks" that are most commonly used in machine vision fields. It is found to be analogous to Multi-Layer Perceptron (MLP), except for the fact that the variation lies in its ability to combine several "locally connected" layers used for feature extraction, accompanied by some "fully connected" layers utilized in the classifying process [11]. It is an effective technique for image recognition and visualization, and object identification. When it is related to deep learning and medical image processing, CNNs are the most commonly used neural networks in AI because they process a large quantity of data and do not require any manual extraction of features. In addition, they do not need any complicated segmentation [12]. In CNNs, the input data is a matrix of pixel values rather than a vector of pixel values, which is used with feedforward neural networks (FFNs).One of the most powerful features of CNNs is the shared weights, which are a group of connections that share the same weights instead of using different weights for each connection. Another feature is the local connection: each neuron does not contact all the neurons in the preceding layer. Alternatively, it only contacts a specific group of neurons to see if they contain the object's feature instead of contacting all cells. This issue produces strong responses to obtain local characteristics in an image input (such as ridges, edges, curves). These two features exceedingly reduce the number of parameters in the network, eventually reducing the training time [13].Three distinct layers make up the CNN's standard architecture, as any CNN model is built using these different layers:

3.2.1. The convolutional layer

It is the fundamental layer for constructing a CNN model. This layer's main purpose is to obtain features from the original input data. It is accomplished using the mathematical operation that is known as "convolution," where this term refers to the combination of two functions to create a new function. This layer contains three matrices: the first is the input image, which is transformed into a matrix (be three-dimensional or grayscale two-dimensional), and the second is called the filters matrix, also named "feature detector" or "kernel." The third matrix is the result of moving the filter matrix with horizontal and vertical steps above the input array (image) to calculate the "dot product" called "activation map" or "feature map". Figure 2 below illustrates the convolution process [14]

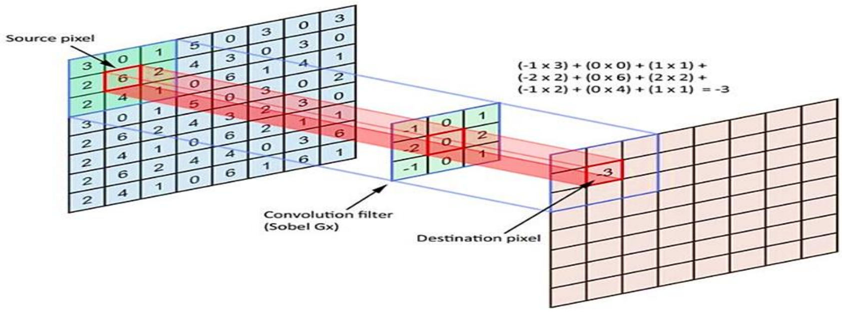


Figure 2. A convolution operation between input and kernel in CNN convolutional layer [14]

Multiple convolution filters are applied for a single input. The resulting activation maps are then combined to obtain the final result for a single convolutional layer. This final result represents input data to the next layer. Each value of the filter matrix is a weight given by default. These values must be different from one filter to another to give different characteristics or features to each matrix from the feature map matrices [3]. There are two types of convolutions: a valid convolution, which is a convolution that does not use padding, and therefore the size of the matrix, will gradually decrease, and a zero or same convolution, which is the type of convolution in which the image size does not change before or after the convolution. The latter type uses the technique of padding [14].

CNN's five convolutional layers comprise a set of activation maps, whose size and number are mentioned in the output size column in Table 1. The activation map is a collection of the 2D array of units. Each unit is created by convoluting and summing one learnable filter of weights, as shown in the "Filter Size" column of Table 1 with all activation maps in the previous layer or input CT image in the situation of the layer. After each convolutional layer, the ReLU is applied as the activating function.

3.2.2. Max pooling layer (also called subsampling or down-sampling)

It is the operation of down-sampling a group of adjacent pixels into a single pixel. This layer is employed after the convolution layer to reduce the size of the image activation maps. There are several common types of spatial layers used, such as Max and Average. The max-pooling determines a spatial area (sub-region) such as a (2×2 window) and selects the biggest element from the rectified Activation Maps within each window. This down-sampling process reduces the activation maps image size from (4 x 4) to (2 x 2). In addition, the average pooling returns the mean value for each sub-region [15]. Pooling layers can solve the problem of overfitting, and max pool has proven to be more robust.

Max-pooling is placed between the convolutional layers and the dropout layers. The dropout layer is used with a small ratio of (0.1). These layers (convolutional and ReLU, max-pooling, dropout respectively) form one of the five blocks in the proposed structure design for CNN. Its main task is to reduce the dimensions by decreasing the dimension of the activation map to a quarter, while preserving the most important details.

3.2.3. Fully connected layer (classification layer)

This layer works in a similar way to the traditional MLP network, as each node has a complete connection to all the nodes in the following layer, hence the names fully connected or dense layers. It is used as a classifier in the last layers of the CNN structure to assess the probability of the object in the image via the Softmax function in the output layer. Other classifiers can also be used, such as SVM [14].

The output of the Max-pooling layer in the fifth block is a 2D matrix, which passes through the dropout layer to be reshaped by the column scan to construct a vector of one dimension with the length of 8× 8× 320= 20480. Next, it is passed as input to a “fully connected” layer. The suggested structure is shown in Table 1, and it comprises 14 consecutive layers divided into two stages based on their work, which are the feature extraction phase and the classification phase.

In this study, the features extraction in the proposed CNN structure (SimpNet model) consists of five successive Conv blocks. The structure for extracting the features is presented in Table 1 from the first row to the tenth row, while the remaining rows represent the classification stage. Each block comprises three layers: a convolutional layer with an activation function (rectified linear unit (ReLU)), the Max Pooling layer, and Dropout layer.

Table 1. The proposed CNN structure (the input and output sizes, the filter size)

Num	Layer name	Input Layer	Output Layer (feature map)	Filter Size, Stride	Param #
1	Convolution 1 & ReLU	(256, 256, 1)	(256, 256, 20)	(3×3),1 90	200
2	Max Pooling1 & Dropout (0.2)	(256, 256, 20)	(128, 128, 20)	(2×2), 2	0
3	Convolution 2 & ReLU	(128, 128, 20)	(128, 128, 40)	(3×3), 1	7240
4	Max Pooling2 & Dropout (0.2)	(128, 128, 40)	(64, 64, 40)	(2×2), 2	0
5	Convolution 3 & ReLU	(64, 64, 40)	(64, 64, 80)	(3×3), 1	28880
6	Max Pooling3 & Dropout (0.2)	(64, 64, 80)	(32, 32, 80)	(2×2), 2	0
7	Convolution 4 & ReLU	(32, 32, 80)	(32, 32, 160)	(3×3), 1	115360
8	Max Pooling4 & Dropout (0.2)	(32, 32, 160)	(16, 16, 160)	(2×2), 2	0
9	Convolution 5 & ReLU	(16, 16, 160)	(16, 16, 320)	(3×3), 1	461120
10	Max Pooling5 & Dropout(0.2	(16, 16, 320)	(8, 8, 320)	(2×2), 2	0
11	Fully connected layer (Flatten)	(8, 8, 320)	20480	/	0
12	Dense layer 1 (512)	20480	512	/	10486272
13	Dropout layer(0.4)	/	/	/	0
14	Dense layer 2 (2) SoftMax	512	2	/	1026 11.100.098

3.3. Classification phase

Two classifiers (SoftMax and SVM) are used in this study to diagnose cases of Covid-19 infected patients.

3.3.1. SoftMax classifier

After the flattened layer of the CNN building, there is a fully connected layer of dense architecture with an activation function (ReLU). The dropout layer with a ratio of (0.4) regulates and prevents the network from overfitting. Finally, the diagnosis of Covid-19 is achieved in the output layer (Dense Layer 2), which is a "fully connected" layer. The output of Dense Layer 2 is passed into the Softmax activation function, which calculates the probability for every category depending on the input CT image. The probabilities obtained from Dense Layer 2 are transmitted into the loss function shown in (1) to calculate the error value, which will be applied to adjust or update the weights through the backpropagation process of training the proposed architecture.

$$loss = -\sum_{i=1}^{n} y_i \log \hat{y}_i \qquad (1) \quad [16].$$

In the training phase of CNN, the CT image classification uses the Adam optimization algorithm and loss function (sparse categorical cross-entropy) to evaluate the network. This also includes reducing the learning rate to improve the validation loss value whenever the model's performance stops improving (decrease on the plateau), as well as early stopping to find the best number of epochs in the training of CNN. The following step is to pass the CT images on the CNN structure in both forward and backward directions within many epochs. This process is determined by the early stopping to decrease the loss (error) between the predicted output of the CNN model and the actual label of the training sample, and to adjust the weights to be used in the testing phase. The output of CNN training is a trained set of weights and kernels for all layers of the network architecture. These trained weights and kernels are stored for the network later in the testing process.
In the test phase of the CNN, the test is performed on the invisible test data. The test algorithm begins with pre-processing. The next step is to pass the CT images on the CNN structure in the forward direction only to extract the features and then classify these images into "Covid-19" (0) and "Non-Covid-19" (1) by using the trained weights in the “fully connected” layers and the trained kernel in the convolution layer that were stored in the training phase and applied later in the test phase.

3.3.2. Support vector machine classifier (SVM)

SVM is one of the supervised types of ML methods commonly used for regression and classification tasks. It is mainly used for detection tasks because it produces high accuracy rates in various applications. SVM is based on the idea of finding an optimal hyperplane (also called decision surface) that divides the data set into two classes in the best way. The distance between the hyperplane and the closest point of any of the data sets is referred to as the margin (this distance should be equal). The data closest to the hyperplane are support vectors, as shown in Figure 3. The goal here is to choose the hyperplane with the most significant margin between it and any point in the training data set, to increase the probability of classifying any new data correctly [17] [18].

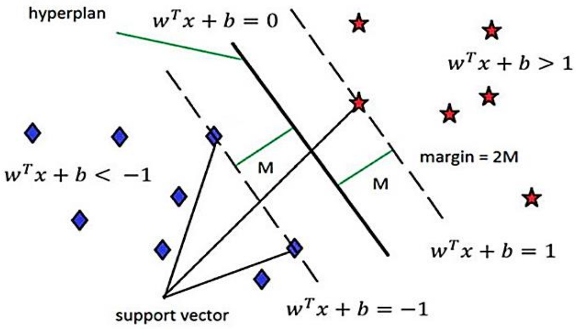


Figure 3. The support vector machine (SVM)

The SVM classifier has been added to the extracted features of CNN's fully connected layer (dense layer 1) to produce results for classifying CT scan images into "Covid-19 or non-Covid-19". This classifier begins with standardizing the feature values extracted (feature vector) from CNN to speed up the processing because these features will be within a specified range after standardization. The CT image classification passes through two phases. In the training phase of the SVM, the representative feature of input data is automatically extracted by using the trained CNN model (features vector of the training set from Dense Layer 1 of a CNN model). The extracted representative feature data and their corresponding labels are input into the SVM model to complete the training of SVM. In a testing phase, the test CT image is classified according to the feature vector of the test set obtained from Dense Layer 1 of CNN and the trained features vector of SVM and returns the class label. SVM makes use of the "radial basis function" as a kernel. In this study, the non-linear SVM is used to classify the Covid-19 data. The idea of non-linear SVM is to convert training data from lower dimensional input to high dimensional output spaces. This method is known as the feature space, which can separate data in linear form. The input data is converted from the input space to the high dimensional feature space using the (RBF, sigmoid, and polynomial) kernel functions.

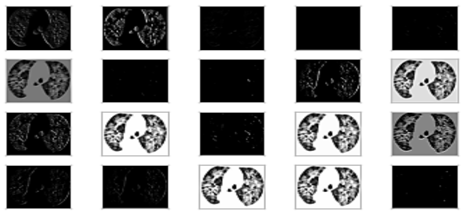
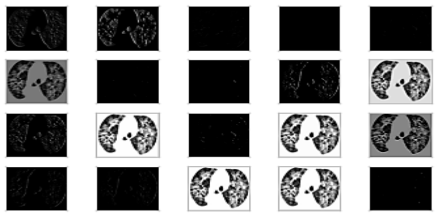
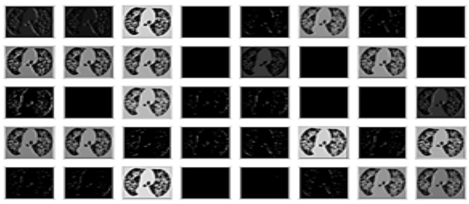
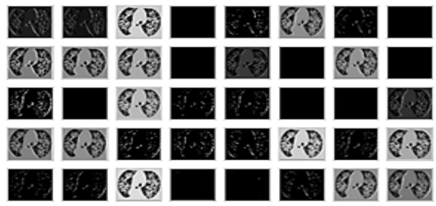
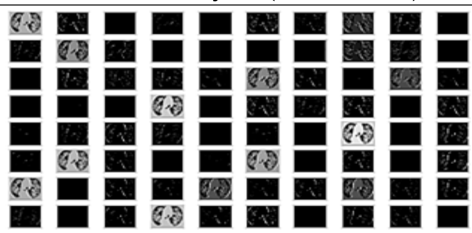
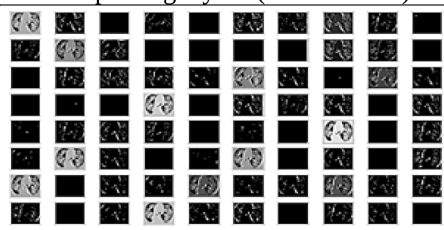
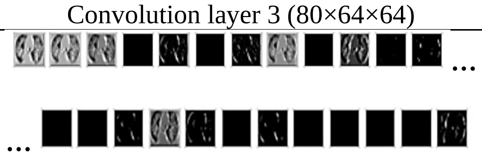
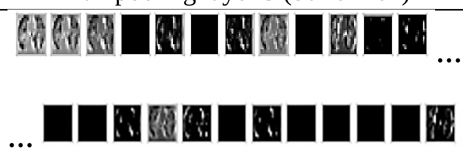
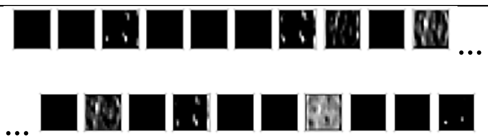
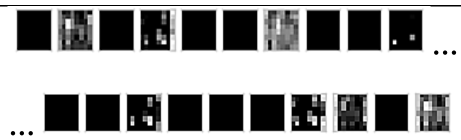
4. Results and discussion

The system's performance outcomes are discussed in this section. There are two steps: results of the proposed convolutional neural network structure steps (features extraction steps), and results of the classification steps (CNN-Softmax and CNN-SVM). The major subjects that will also be covered in this section are the CT image database and their division, detailed outputs for each step in the proposed method, and the evaluation of the proposed system by calculating performance metrics using the CT images.In this method, the CT images were taked from the open-source GitHub repository presented by Dr. Joseph Cohen for the experiment on 216 COVID-19 patients (Zhao, Jinyu, et al., 2020). The dataset is comprised of 746 CT scan (349 Covid-19 CT scan and 397 non-Covid-19 CT scan). The datasets are divided into two samples: the training data sample is 70% of the total dataset (521 CT scans), and the testing data sample is 30% (225 CT scan).

4.1. Results of feature extraction

The feature extraction steps are performed using CNN, which consists of five successive Conv blocks. Each block is comprised of three layers: the Convolutional layer with ReLU activation function, the Max Pooling, and the dropout layer. Table 2 illustrates the output of the COVID-19 CT image for each layer of the five-block layers.

Table 2. The outputs of feature maps for the COVID-19 sample

Block / Layer	**Feature Maps of the CT scan**	
 **Block 1**	 Convolution layer 1(20×256×256)	 Max pooling layer 1(20×256×256)
Block 2	 Convolution layer 2(40×128×128)	 Max pooling layer 2(40×128×128)
Block 3	 Convolution layer 3 (80×64×64)	 Max pooling layer 3 (80×64×64)
Block 4	 Convolution layer 4 (160×32×32)	 Max pooling layer 4(160×32×32)
Block 5	 Convolution layer 5 (320×16×16)	 Max pooling layer 5(320×16×16)

The convolution layer in the CNN model, as presented in Table 2, extracts the features or manifestations of the COVID-19 CT images by passing many different filters over a CT image, such as edges detection, vertical, horizontal and diagonal lines, curves, corners, color contrast sensitive filters, and Gabor-like filters. Each of these filters produces a feature map that indicates spatial patterns where the feature is located. Then, the feature map passes through the non-linear activation function (ReLU). The size of each filter is (3, 3), and the number of kernels in each layer are (20, 40, 80, 160, 320), respectively, as shown in Table 1. The Max Pooling layer decreases the computational power by declining the dimensions of the features map to half because the kernel size equals (2, 2), as shown in Table 2. This contributes to the reduction of the overfitting problem.

4.2. Results of the classification phase

Softmax is the first method for classifying CT images, and it comprises the remaining four layers of the CNN architecture as follows:

- Flattening layer: converting the activation maps (three dimensions) to a vector (one dimension) so the output is $8 \times 8 \times 320 = 20480$.
- Fully connected layer of the Dense architecture (Dense layer 1) with an activation function (ReLU); there are (512) units.
- The drop-out layer with a ratio of (0.4) to control and prevent the network from overfitting during the training procedure of the system.
- The output layer (Dense layer 2) is a "fully connected" layer with number of units (2). The output of this layer is passed into the Softmax activation function to compute the probabilities for each class according to the input image. The probabilities are passed to the loss function (sparse categorical cross entropy) to calculate the error value which will be applied to adjust or update the weights through the backpropagation process.

In the training phase, the CT image classification uses the Adam optimization and learning rate reduction to improve the validation loss value whenever the model's performance stops improving (decrease on the plateau), batch size = 64, in addition to early stopping to find the best number of epochs (maximum = 50). The training is performed on both the augmented data and the original data. Figure 4 illustrates the evaluation of the CNN performance in accuracy scores, showing the total amount of errors predicted by the model. The accuracy value for training or validation did not change. It stabilized at a specific value after 15 epochs, so the training was stopped.The learning curves (loss of training and validation) plots in Figure 5 illustrate the good fit condition when training the model on the augmented data. The loss of training and the loss of validation depreciate to the point of equilibrium, and the gap is minimal between the two-loss values. It is potentially the persistent training of a good fit that would produce a problem of overfitting, so an early stopping was used when training the model.

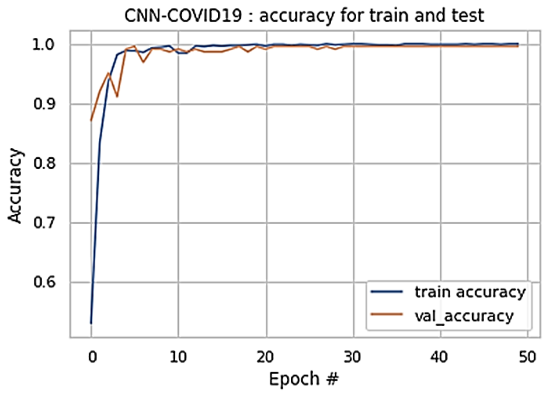


Figure 4. Accuracy learning curves of train and val

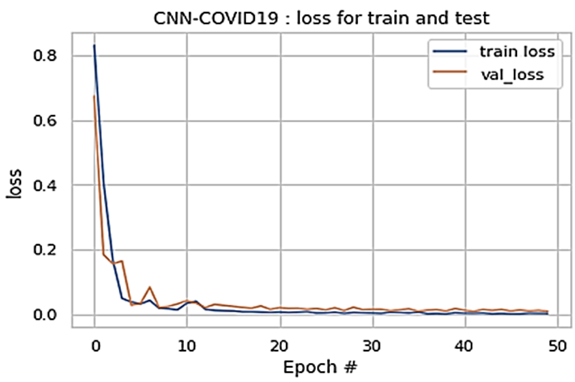


Figure 5. Loss of training and validation

In the testing phase, all test samples that are 30% of the database (225 CT images) will be passed to the system without their labels being tested. In the classification stage, the results of the proposed system output will be presented using two classification methods applied to the test sample: SoftMax function and SVM for detecting cases infected with COVID-19. One of the significant challenges of assessing computer and human interfaces is determining the evaluation standards and metrics that make various systems and concepts comparable, and determining the system's weaknesses. Any classification systems are evaluated based on the performance compared to the actual class's samples information. The efficiency of the classification algorithms can be assessed through various metrics using the samples with known class information. Some measures are commonly used for evaluation. In this work, the accuracy, precision, sensitivity, specificity, and AUC are utilized in the evaluation of the effectiveness of the proposed approach.In this evaluation, True Positive (TP) represents the proper categorization in the right (positive) prognosis such as COVID-19 categorized as COVID-19, False Positive (FP) is a wrong classification of a positive diagnosis, such as COVID-19 categorized as Non-COVID-19. False Negative (FN) is a wrong classification of negative diagnosis such as NonCOVID-19 categorized as COVID-19. True Negative (TN) represents the proper categorization in the passive diagnoses, such as Non-COVID-19 categorized as Non-COVID-19 [19]. Figure 6 and Figure 7 represent the confusion matrix using the SoftMax function and SVM classifier.

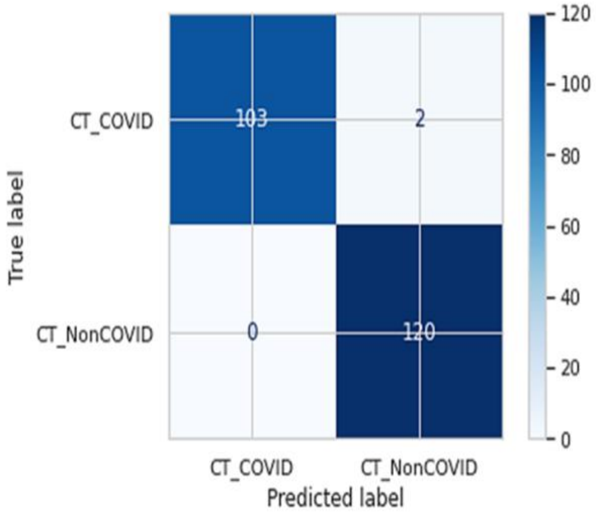


Figure 6. Confusion matrix using softmax function

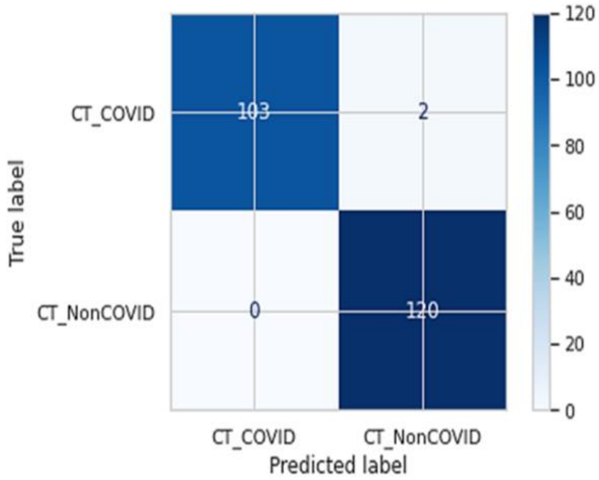


Figure 7. The confusion matrix of the test sample using SVM

The performance measures using CNN-SoftMax are compared with the results of using CNN-SVM in Table 3. It is shown that the CNN-SVM achieved higher results than CNN-SoftMax. CNNs have convolutional layers, as these layers contain important filters for extracting features from the CT image. Therefore, they have been adopted to extract features, but they suffer from high parameter adjustment and overfitting issues. The SVM is built on the principle of finding the optimal hyperplane for separating a data set into two groups in an efficient way. To maximize the margin results (the distance between the hyperplane and the closest point of any of the data sets), the SVM provides the ability of generalization better than using the SoftMax function as a classifier. The aim is to select the hyperplane with the most considerable margin between it and any point in the training dataset, in order to enhance the probability of correctly classifying new data.

Table 3. Comparison results between CNN-SoftMax and CNN-SVM

Method	**Sensitivity**	**Specificity**	**F1-score**	**AUC**	**Accuracy**
CNN- SoftMax	1.00%	97.5%	98.4%	98.7%	98 %
CNN-SVM	98.1%	1.00%	98.3%	99.0%	**99.1%**

Table 4 compares various deep learning-based Covid-19 diagnostic methods with the proposed system performance using the same dataset of CT images. It has been noticed that the proposed system accomplished higher performance rates than the alternative existing systems. The main reasons for obtaining these enhanced results can be summarized as follows. Firstly, the CNN architecture design shown in Figure 1 involves identical blocks of layers that are stacked to capture discriminative features and use a dropout layer after each Max Pooling layer to improve accuracy and generalization. Secondly, the overfitting problem was prevented by using early stopping technology during a train of CNN and Dropout layer, which is the problem that most CNN models suffer from. Thirdly, the number of parameters obtained in the system reached (11,100,098), which is not much as compared to the number of other literature models.

Table 4. Compares the results of the proposed study to those of other studies

Study		**Sensitivity%**	**Specificity%**	**AUC%**	**Accuracy%**
Zhao et al., 2020		-	-	98	89
Anwar and Seemab, 2020		89.5	89.5	89.5	89.7
Loey, Gunasekaran and Nour, 2020		77.66	87.62	82.64	82.91
Mishra et al., 2020		88.3	88.3	88.3	86
Bhansali, Rahul and Duke, 2020		89.38	-	-	92
Jim et al. , 2020		-	-	-	92.5
Amyar et al., 2020		94	79	86.5	86
Proposed system	CNN-SVM	98.1	1.00	99.0	**99.1**
	CNN-SoftMax	1.00	97.5	98.7	98

5. Conclusions and future work

The essential conclusions of the results obtained from adopting the suggested method for COVID19 diagnosis in the CT scan can be outlined as follows. The evaluation of the suggested method can be done using CNN-SoftMax function and CNN-SVM classifiers: the specificity, sensitivity, accuracy rates are 97.5%, 1.00%, and 98% with CNN- SoftMax and 1.00%, 98.1%, and 99.1% with CNN-SVM, all respectively. The experiments of the CNN-SoftMax and CNN-SVM are compared to assess the performance. It has been found that the CNN-SVM algorithm is more accurate than using the CNN-SoftMax algorithm. The proposed model achieved a higher accuracy with fewer parameters of (11.100.098) and required less computational power. The proposed method is highly accurate using CNN-Softmax or CNN-SVM, which reduces the problems of limitation in the number of Covid-19 cases to be treated, allowing the system to be used in real-time.

Declaration of competing interest

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

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