Original Article

Automatic Diagnosis of COVID-19 Pneumonia using Artificial Intelligence Deep Learning Algorithm Based on Lung Computed Tomography Images

Mohammad Amiri[1], Manizheh Ranjbar[2], Gholamreza Fallah Mohammadi[3]

[1]Assistant Professor, [2]Lecturer, Department of Computer Engineering, Technical and Vocational University, Tehran, [3]Department of Radiology, Faculty of Allied Medicine, Mazandaran University of Medical Sciences, Sari, Iran

Abstract

Background: The lung computed tomography (CT) scan contains valuable information and patterns that provide the possibility of early diagnosis of COVID-19 disease as a global pandemic by the image processing software. In this research, based on deep learning of artificial intelligence, the software has been designed that is used clinically to diagnose COVID-19 disease with high accuracy. **Methods:** Convolutional neural network architecture developed based on Inception-V3 for deep learning of lung image patterns, feature extraction, and image classification. The theory of transfer learning was utilized to increase the learning power of the system. Changes applied in the network layers to increase the detection power. The process of learning was repeated 30 times. All diagnostic statistical parameters of the diagnostic were analyzed to validate the software. **Results:** Based on the data of Imam Khomeini Hospital in Sari, the validity, sensitivity, and accuracy of the software in diagnosing of affected to COVID-19 and nonaffected to it were obtained 98%, 98%, and 98%, respectively. Diagnostic statistical parameters on some data were 100%. The modified algorithm of Inception-V3 applied to heterogeneous data also had acceptable precision. **Conclusion:** The proposed basic architecture of Inception-v3 utilized for this research has an admissible speed and exactness in learning CT scan images of patients' lungs, and diagnosis of COVID-19 pneumonia, which can be utilized clinically as a powerful diagnostic tool.

Keywords: *Computed tomography image, COVID-19 pneumonia, deep learning, machine learning*

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Introduction

The severe acute respiratory syndrome coronavirus 2 (SARS-Cov-2) virus was first transmitted from rhinolophus bat to humans in December 2019. The outbreak of the coronavirus center was announced in the seafood sales center in Wuhan City, Hubei Province of China, and spread quickly worldwide. In addition, the WHO declared it as a pandemic disease in March 2020.[1] A particular radiographic pattern in the lung computed tomography (CT) scan images of influenced patients has led to high sensitivity and specificity of this imaging method compared to the reverse transcription polymerase chain reaction (RT-PCR) method in diagnosing COVID-19. According to the WHO report test, in the positive cases of the disease, the RT-PCR test has a low diagnosis power in the early stages. In a report from China, the sensitivity of CT scan imaging was 97% within 1041 patients whose test was positive by the RT-PCR method.[2] The CT scan images have an extremely high diagnostic value due to their cross-sectional nature and elimination of overlap between adjacent tissues. Due to the relatively high occurrence of this disease, early detection could provide a base for reducing the epidemic and accelerating the onset of treatment that leads to a significant decline in mortality. Specific symptoms of the disease on CT images include ground-glass opacities, multiple mass-like consolidations with (or without) interstitial changes that are typically distributed in the peripheral parts.[2,3] Particular findings of COVID-19 disease on CT scan make it noticeable from other pneumonic viruses. However, coronavirus symptoms that overlap with other pneumonia make it impossible to differentiate them with visual tools.[4] However, artificial intelligence tools and deep learning technology can provide differential diagnoses among various types

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Address for correspondence:
Dr. Gholamreza Fallah Mohammadi, Department of Radiology, Faculty of Allied Medicine, Mazandaran University of Medical Sciences, Sari, Iran.
E-mail: gh.fallah@mazums.ac.ir

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of pneumonia with high precision.[5] We used convolutional neural network models of artificial intelligence to categorize the samples of CT scan images of patients with either coronavirus or nonaffected patterns and to diagnose the disease provided software with high accuracy quickly. The designed software can prepare an early diagnosis of the lung involvement in patients and announce an early warning for patient quarantine. As a result, other people close to them will not be at risk; at this stage, diagnosis and treatment can be presented. Diagnostic interactive design software in the field of health provides a proper base for using it incomprehensible warning comparisons (color comparisons of conflict intensity) and mobile phones, Tele-imaging, and picture archiving and communication systems.

Materials and Methods

Patients' information and computed tomography scan images

Of these images, 2204 CT scan images with a definitive COVID-19 disease were related to 474 patients, and 2404 CT scan images with the diagnosis of a normal lung or axial image of non-COVID-19 were diagnosed related to 274 patients. The CT scan images were chosen from 4 databases including the data of Imam Khomeini hospital of Sari and global training data including Sars,[6] COVID-CT,[7] and a part of COVID-CT-MD (MD)[8] related to patients with COVID-19. Both COVID-CT and Sars datasets are the biggest public datasets so far. The diagnosis of extracted images from mentioned sources was based on observation by radiologists, laboratory, and clinical markers, which is accounted as a gold standard for diagnosing COVID-19. Axial CT scan images were analyzed with sharpen kernel, lung window, and a thickness of 1–3 mm. 80% of all CT scan images as training data were randomly examined for deep learning by the software and 20% as test data to validate the software and assess its function. We used this ratio for all tests in this article. E-convolution neural networks require an extensive data set for training, and currently, there are no available medical images in this area. As a result, by applying transfer of learning theory at the initial stage, I considered the Premodel training on natural images from the ImageNet dataset to improve system detection and performance. ImageNet is a set of more than 17 million images with high-resolution, which is increasing day by day. This dataset includes about 22,000 categories.[9]

The structure of the network

According to deep learning, a model was presented using CT images for image classification. The process of analyzing CT information by the software and the basis of its function is shown in Figure 1. The primary foundation of the network is based on the Inception-V3 architecture, utilized to diagnose COVID-19 by applying changes to the last layers and reeducation of the network with CT images. The inception module has parallel layers, which usually include convolution layers of three different sizes and one Max-pooling layer. Thus, information can be extracted in separate layers. The structure of the inception network is such that in addition to increasing the network depth, it also decreases the number of network parameters, which reduces the computational complexity, boosts the precision and efficacy of the network, and prevents over-fitting. Consequently, this structure has been widely applied in medical image processing in recent years.[11-15] The general structure of the proposed architecture is shown in Figure 2. The input size of this network is images of 299 × 299 with three channels by default.[16] The first layer includes the convolution and pooling layers, and then, there are various modules of inception[16]. In the preprocessing block, for Sari and MD datasets, the Dicom images convert to Jpeg image, and in addition, the contrast normalization applied for all datasets in the Inception-V3 architecture factoring immense convulsions to smaller ones applied for improving the performance of Inception architecture. In fact, in this architecture, the Inception module substitutes the larger filters (such as filters of 7 × 7 × 5 × 5 size) that are computationally expensive with the smaller sequential filters with the same function. For instance, a 3 × 3 convolution is replaced by two convolutions 3 × 1 and 1 × 3, and this replacement provides a base for reducing the number of parameters and boosts the network training speed.[10] Figure 3 illustrates the structure of Inception-V3 modules.[10,17] In Figure 3a, the invoice module of 5 × 5 filters to two 3 × 3 filters, in (3-b) the invoice module for convolution with k × k dimensions, and in Figure 3c, an expanded filter bank has presented to boost the size of views. The filter banks in the module have been developed to eliminate bottlenecks; they have become wider instead of deeper. If the module becomes more profound, it leads to extreme lessening of dimensions, and therefore, loss of useful information. According to Figure 3, if the module becomes more profound, it leads to excessive lowering of dimensions, and thus, loss of helpful information

Changes were made to generate a learning model in the network structure in diagnosing affected or nonaffected to COVID-19 and network training. These changes include freezing the layers (no permission for a change), eliminating layers, and creating new ones. At the end of the model, one layer of average pooling and three layers of (Fully Connected [FC]) were added to generate new layers. The first and second FC layers had dimensions of 1024 and 512 neurons, respectively, the ReLu activation function and the last FC layer was with dimensions two and SoftMax activation function. The value two represents the number of distinct classes in the classifier section of the deep learning model. First, the network weight is randomized for the added layers. The freezing operation was presented on all convolution layers of the pretrained model and

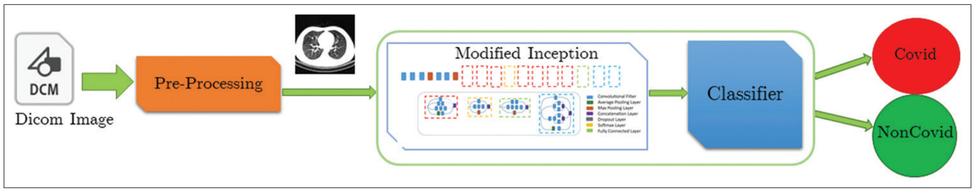

Figure 1: The process of assessing computed tomography scan images to diagnose COVID-19 disease

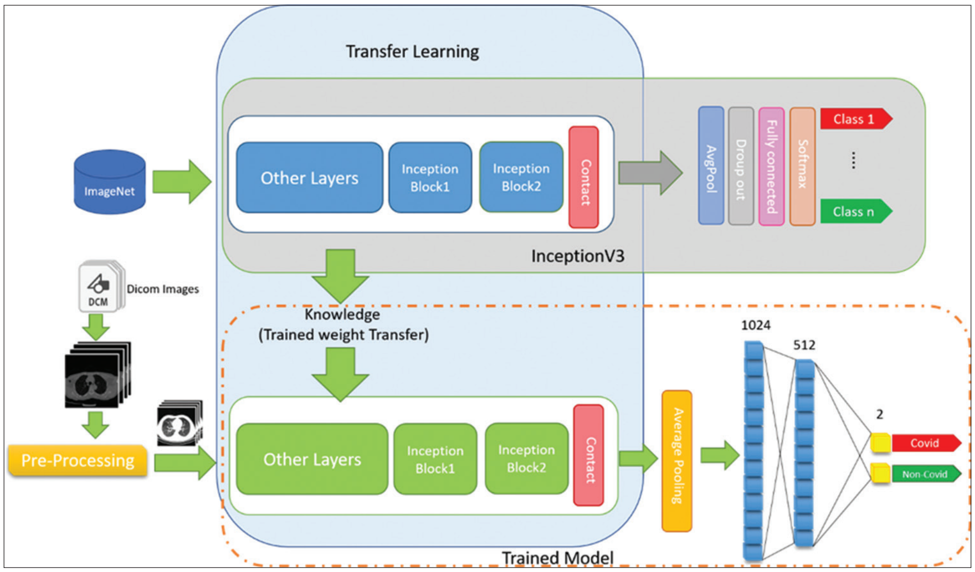

Figure 2: Apply inception-V3 for computed tomography images classification. The last two modules and three fully connected layers were trained using computed tomography images

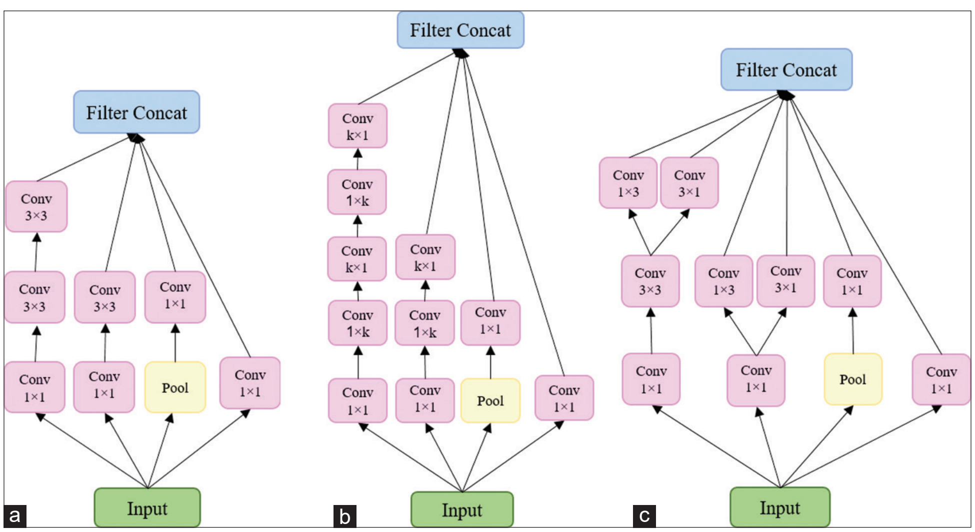

Figure 3: Structure of Inception-V3 modules (a) by replacing 5 × 5 convolutions with two 3 × 3 convolutions; (b) by factorization of convolution filters k × k; (c) has expanded with filter bank outputs[1]

trained the network for batch size = 10, 15 rounds. Based on the experimental observations, a selection of 15 rounds has been completed. At this stage, only the added layer parameters' values are randomly initialized, changed, and well trained. The network convolution layer of parameters was fine-tuned. We only trained two upper inception layers of the Inception-V3 network with added layers for such a purpose. As a result, we freeze all lower layers of the network and eliminate two layers above the inception networks from freezing. Again, trained the network for batch size = 10, 30 rounds. The trained networks act as feature extractors, and the last two layers (FC layers) will perform the categorization. In this research, the capability classification systems of Support Vector Machine (SVM), Kernel-SVM (with Polynomial (Poly), Radial Basis Function (RBF), Sigmoid) kernel classification systems

Table 1: The dataset used in this research and its characteristic

Sample number/dataset	COVID CT	Sars	MD	Sari	Total
Total number of patients	271	120	307	50	748
Number of patients with COVID-19	216	60	171	27	474
Number of normal patients	55	60	76	23	274
Number of patients with CAP			60		
Number of lung images with COVID-19	349	1252	148	455	2204
Number of lung images without COVID 19	397	1230	322	455	2404

CAP - Community-acquired pneumonia; CT - Computed tomography; MD – Covid CT MD dataset

Table 2: Diagnostic parameters to examine the correlation between deep learning software and standard methods in COVID 19 diagnosis using Sari dataset (*n*=182)

	Predicted COVID	Predicted non COVID	Total
Actual COVID	TP=90	FN=1	91
Actual non COVID	TN=88	FP=3	91
Total	178	4	

TP- True positive, FN- False negative; TN- True negative; FP- False positive

Table 3: Correlation of deep learning model in comparison with the standard diagnostic method in COVID 19 diagnosis

F1-score (%)	Specificity (%)	Sensitivity (%)	Accuracy (%)	Dataset
79	79	80	79	COVID CT
82	74	91	74	Sars
100	100	100	100	MD
98	99	97	99	Sari

CT – Computed tomography; MD – Covid CT MD dataset

were examined in recognizing and analyzing input data. These systems (Incept-SVM) categorize the obtain output from the middle layer of the Inception-V3 deep learning network. The proposed system efficiency was also analyzed by adding layers to the network's end, with the value Epoch = 25. Epoch in a deep learning system is described as the number of repeat trainings, in which the particular neural network completes an overview of the entire training set.[18] Loss and accuracy analysis was presented on data from three groups: MD, Sari, and COVID-CT with the 15 repetitions of training rounds of the network upper layer, 30 repetitions of network training, and the number of batches equal to 10. According to the chosen values of the experimental observations in all experimental training, training in thirty rounds coverage well. This analysis is utilized to verify the system's accuracy and distance of the estimated value from the actual value

Software validation

In this research to assess the performance of the proposed method, accuracy criteria with equation (TP + TN)/(TP + FP + TN + FN), sensitivity with equation TP/(TP + FN), its specificity with equation TN/(TN + FP) and F1-score (F1) with 2TP/(2TP + FP + FN) has been calculated. In the mentioned equations, TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

The code of ethics

The ethics committee has approved the current research of Mazandaran University of Medical Sciences with the (Approval ID), IR. MAZUMS. REC.1399.664.

Results

Data set features that have been assessed in this research are shown in Table 1.

Images with COVID and non-COVID involvement were analyzed using the proposed method. Accuracy, sensitivity, and precision for Sari datasets were obtained 0.98, 0.98, and 0.98, respectively. Table 2 illustrates the findings from the analysis of images and diagnostic parameters by the proposed method.

The analysis of laboratory markers and reports by a radiologist is described as a standard method. Table 3 illustrates the correlation of the deep learning model in comparison with a standard diagnostic method in the form of statistical parameters for four datasets COVID-CT, Sars, MD, and Sari. The multiple classification systems were examined for classifying the features extracted from the images in the proposed method. This classification system includes SVM, Kernel-SVM (kernels Poly, RBF, Sigmoid). The findings of this research are illustrated in Table 4. This research was presented on three datasets: COVID-CT, MD, and Sari. Accuracy of adding various layers to the end of the proposed network was utilized to identify the images features in Table 5. The survey was conducted on the Sars datasets.

Figure 4 illustrates the convergence of loss and accuracy criteria of the proposed algorithm. It was conducted on three datasets MD, Sari, and COVID-CT, for the reputation of 15 rounds of training for top layers of the network, the reputation of 30 rounds of network training, and the number of batches equal to ten. In this research, we analyzed the generalizability of the proposed model on the heterogeneous data. The model should be capable of generalizing on other datasets. This provides a base for analyzing the proposed model behavior and its performance in dealing with new

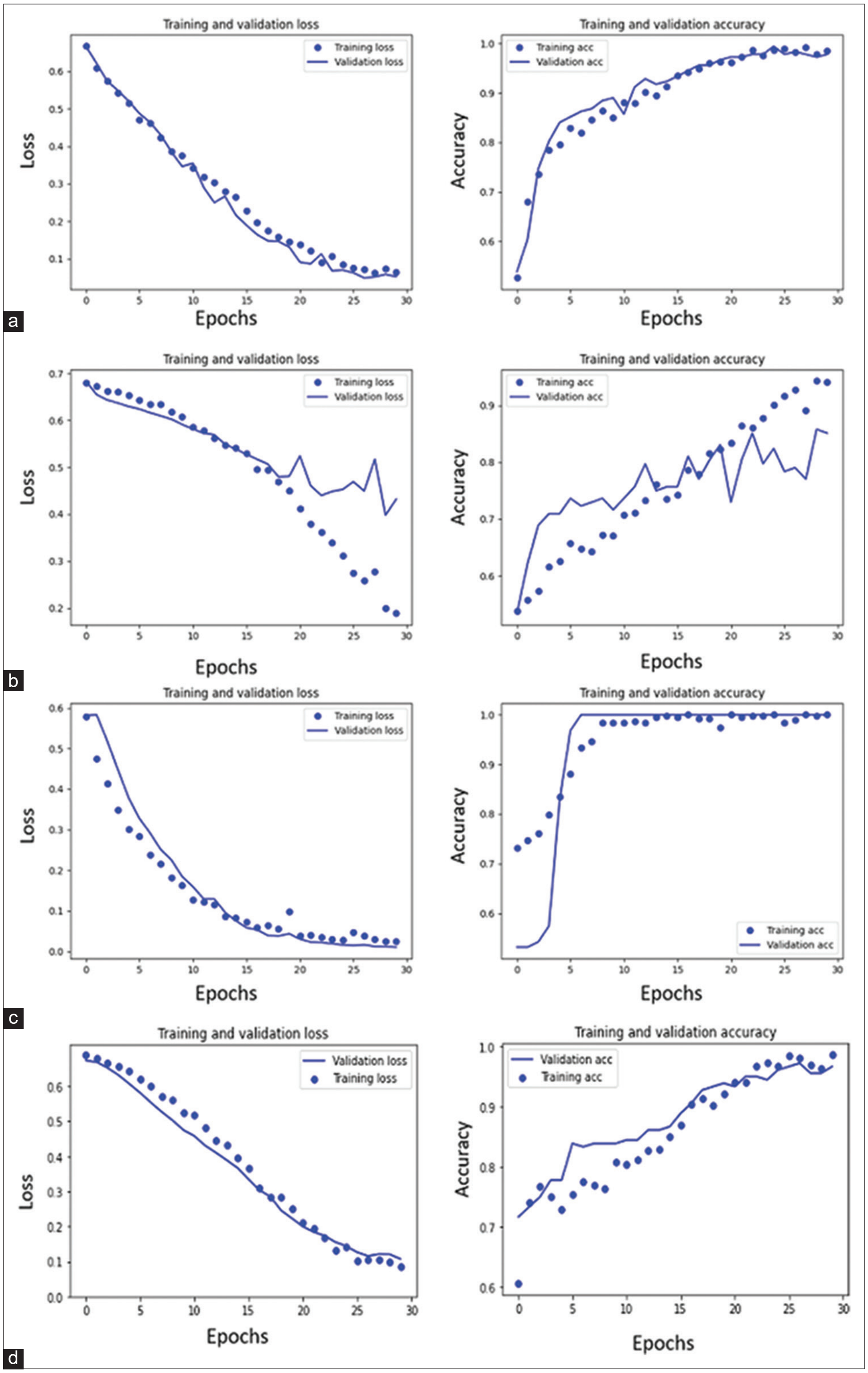

Figure 4: Training loss and accuracy evaluation of proposed method on three data sets: (a) Sari (b) COVID-computed tomography (c) MD (d) severe acute respiratory syndrome

CT images provided by various devices. Table 6 illustrates the findings on two various datasets. In each experiment, we have chosen one of the Sars, COVID-CT, MD, and Sari datasets as the test dataset and one of the Sars, COVID-CT, and MD datasets as training data.

Discussion

In the Inception-V3, the architecture utilized to design COVID-19 disease diagnosis software besides general learning; parallel learning in the layers. This makes learning faster than other models, including network model (Visual

Table 4: Accuracy (percentage) resulting from the use of various classification systems on the dataset COVID computed tomography, MD, and Sari

Dataset/classifier	Inception	SVM	K-SVM (polynomial)	K-SVM (RBF)	K-SVM (sigmoid)
COVID CT	79	80	71	78	79
MD	100	100	99	100	100
Sari	98	99	98	99	96
Sars	74	73	72	73	72

CT – Computed tomography; SVM – Support vector machine; RBF – Radial basis function; MD – Covid CT MD dataset

Table 5: Accuracy of adding various layers to the end of the proposed network

Epoch	Number of layers	Dimension of each layer	Accuracy (%)
25	2	1024-500	85.28
25	4	1024-500-256-128	84.07

Table 6: Cross dataset results

Dataset	Accuracy	Precision	Recall	F1-score
Train				
Test	69.57	85	52	44
COVID CT				
MD	54.57	55	55	54
Sars	54.62	55	55	54
Sari	45.31	46	46	44
Sars				
COVID CT	39.15	48	48	39
MD	59.67	68	60	54
Sari	51.88	47	49	39
MD				
COVID CT	49.93	62	51	35
Sars	39.45	26	39	29
Sari				

CT – Computed tomography; MD – Covid CT MD dataset

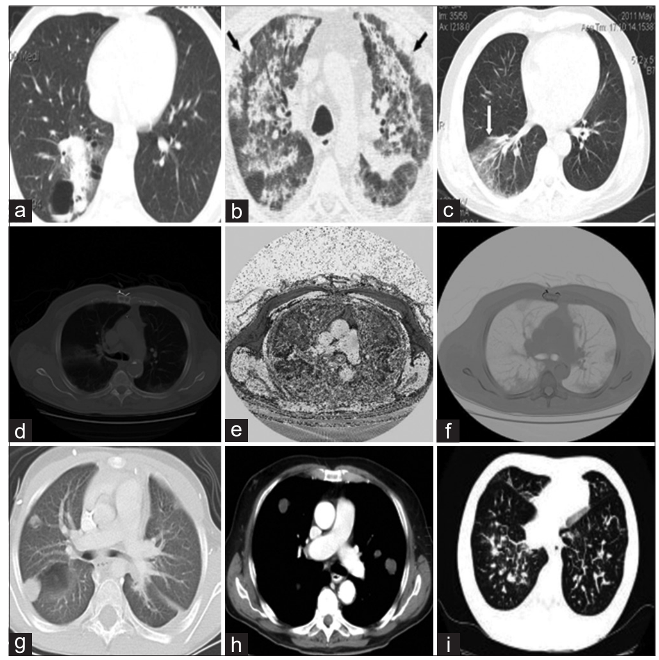

Figure 5: (a-c) Images with text data. (d-f) Dicom images with different image viewer software. (g-i) Images with different contrast

Geometry Group [VGG] Network).[17] On the other hand, the volume of a pretrained model is much lighter than the pretrained VGG model.[17] Transfer of learning could be considered a notion for using the weights of the pretrained networks, improving the efficiency of the model, or achieving a particular task including medical imaging or audio event detection in real-world environments.[11,16,19,20] According to Table 4, using the SVM algorithm as a classifier has no efficient impact on boosting the efficiency of our proposed algorithm. However, it amplifies the number of calculations. The algorithm efficiency was evaluated on all three datasets COVID-CT, MD, and Sari; thus, the maximum accuracy of the algorithm Incept-SVM was obtained 80, 100, and 99% for the three datasets, respectively. The findings are close to the proposed method's results with an accuracy of 79, 100, and 98%, respectively, for three datasets. The efficiency was also achieved by K-SVM = "poly" algorithm with 71% accuracy for COVID-CT, 99% for MD and 98% Sari, and not only lead to a boost in the efficiency but also decreased the accuracy of the proposed method. According to Table 5, for the same number of Epochs equal to 25, the system accuracy reduces due to the change in network layers from two to four layers. This can be due to the increased number of learning parameters by boosting the number of layers; thus, the problem becomes more complicated. According to Table 6, the model's efficiency reduces by evaluating the general ability of the model and if the model is trained on various data sets. This would be due to the differentiation in distinguishing the presence or absence of COVID-19 in CT images, which is accomplished from imaging of different devices with dissimilar protocols. The accuracy and precision values on the MD set as a test dataset and COVID-CT considered as training dataset obtained with an accuracy of 69.57% and a precision of 85%. The maximum recall value for the Sari dataset as a test and Sars as a training dataset was calculated to equal 60%. As a result, Sars data can be for training in the case of insufficient images of Imam Hospital devices. Table 7 is comparing other utilized on the implementation method, the number of data sets analyzed, the type of medical images, and the ability to generalize the evaluation on heterogeneous datasets.

Table 7: Comparison of various algorithms for the diagnosis of COVID disease 19

The algorithm	Architecture	Dataset	Types of images	Accuracy	Cross data	Accuracy of cross data
Maghdid H.S. *et al*.[21]	AlexNet	Five different small datasets	X-ray, CT	98%	No	-
COVID-FACT[22]	UNet+capsule networks	MD	CT	90.82	No	-
CT-Caps[23]	UNet+capsule networks	MD	CT	90.8	No	-
iSARF[24]	VB-Net+decision tree+combine of SVM, LR, NN, SARF	Personal dataset	CT	87.9	No	-
Gozes *et al*.[25]	UNet+ResNet50	Zhejiang province, China/El-Camino Hospital (CA)/HUG/Chainz	CT	AUC=0.948	No	-
COVID-CAPS[26]	Capsule networks	NIH chest X-ray dataset	X-ray	98.3	No	-
Efficient COVID Net[27]	Efficient learning	COVID CT/Sars	CT	87.68	Yes	56.16
COVID CT-Net[28]	Modified ResNet-56	Sars-Cov-2	CT	92	No	-
Bit-M[29]	ResNet-V2	COVDx CT-2A	CT	99.2	No	-
Our study	InceptionV3	COVID CT/Sars/MD/Sari	CT	99	Yes	69.57

CT – Computed tomography; SVM – Support vector machine; MD- Covid CT MD dataset; LR: Logistic regression, NN- Neural network; SARF- Size aware random forest

Table 8: Comparison of different algorithms on heterogeneous datasets

Method	Dataset: Train	Test	Accuracy	Precision	Recall
Efficient CovidNet[8]	CovidCT	Sars	45.25	54.39	46.39
	Sars	CovidCT	58.31	61.03	54.90
Proposed Method in our study	CovidCT	Sars	54.57	55	55
	Sars	CovidCT	45.31	46	46

Since among the algorithm, the only presented algorithm in[27] named Efficient CovidNet has evaluated the algorithm with heterogeneous data sets and in other works (e.g., in[28,29]) also the result of accuracy is better, but consider that they used the same datasets both for training and test also they separated train and test data. For instance, in,[28] they used only SARS-CoV-2 CT scan dataset, which has been collected from real patients in the hospitals from Sao Paulo, Brazil both for train and test. Furthermore, thus, in Table 8, a comparison of our proposed model has shown the mentioned method for evaluating heterogeneous data sets. The network accuracy on the COVID-CT dataset was 58.31% after training the efficient COVID Net model by Sars data set. However, for our proposed method, this value is equal to 45.31%. While after training the Efficient COVID Net model by COVID-CT data set, the network accuracy on the Sars dataset was about 45.25. However, in the proposed method, the accuracy is 54.57%. While after training the Efficient COVID Net model by COVID CT data set, the network accuracy on the Sars data set was about 45.25. However, in the proposed method, the accuracy was 54.57%. Due to the use of different algorithms in the feature extraction and working on datasets imaged by diverse equipment, various models extract features adequate with the trained dataset. They may not be appropriate for heterogeneous test data. Thus, under the circumstances, one method does not necessarily have the advantage over other methods. The accuracy of the proposed algorithm for the COVID-CT dataset is equal to 79%. Out of 74 CT images of COVID 19, 65 were correctly detected, and out of 74 CT images of non-COVID 19, 52 were appropriately detected. In the Sars dataset, out of 248 CT images of COVID, 19, 65 non-COVID were detected, while from 248 non-COVID CT images, only 18 were detected. Only four errors were reported in the Sari dataset, and no errors were reported in the MD dataset. One of the significant obstacles to producing comprehensive and complete software to help specialists diagnose COVID 19 disease more quickly and precisely is the lack of a comprehensive data set of high quality. Most existing data sets, including images extracted from the papers and COVID-19 images provided by hospitals, have been extracted using various medical equipments. Many are accessible in jpg or png file format based on how the information is removed from the original file. Much information has been deleted during the transmission. Images in this dataset have no standardization for image size and contrast. The images in this data set have extremely diverse distinctions [Figure 5 g, h, and i]. Apart from this, some images including text information that may interfere in model training [Figure 5, a, b and c]. According to the functions and Libraries in programming languages, some information obtained from a DCM file can be different [Figure 5d, e, and f]. These elements influence how the learning system works and can influence the final results.

Conclusion

Based on the patient's CT scan image, the diagnosis of COVID-19 disease has higher accuracy and diagnostic speed than other methods. In this research, the software was designed using image-processing algorithms and deep learning capable of speedily and accurately diagnosing COVID 19 disease from patient CT scan information. The modified Inception-V3 architecture utilized in this research has an admissible speed in learning pneumonia patterns of patients with COVID 19. This research uses data transmission by obtaining more pretrained information, and utilizing 4 data sets has a minor error in predicting the CT image of the patient. Software design with high accuracy and diagnostic speed provides a good base for physicians in the initial evaluation of patients and plays an essential role in controlling the COVID-19 pandemic. This software can be used in clinical studies.

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Conflicts of interest

There are no conflicts of interest.

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