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Hybrid Artificial Intelligence Approach for COVID-19 Diagnosis from CT Images: Deep Networks and Classification Analysis

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ABSTRACT

Using lung images obtained by computed tomography (CT), this study aims to detect coronavirus (Covid-19) disease with deep learning (DL) techniques. The study included 751 lung CT images from 118 Covid-19 patients and 628 lung CT images from 100 healthy individuals. In total, 70% of the 1379 images were used for training and 30% for testing. In the study, two different methods were proposed on the same dataset. In the first method, the images were trained on AlexNet, VGG-16, VGG-19, GoogleNet and a proposed network. The performance metrics obtained from the five networks were compared and it was observed that the proposed network achieved the highest accuracy value with 95.61%. In the second method, the images were trained on VGG-16, VGG-19, DenseNet-121, ResNet-50 and MobileNet networks. Among the image features obtained from each of these networks, the best 1000 features were selected by Principal Component Analysis (PCA). The best 1000 features were classified with Random Forest (RF) and Support Vector Machines (SVM). According to the classification results, the best 1000 features selected from the features extracted by the VGG-16 and MobileNet networks were obtained with the highest accuracy rate of 93.94% using SVM. It is thought that this study can be a helpful tool in the diagnosis of Covid-19 disease while reducing time and labor costs with the use of artificial intelligence (AI).

1. Introduction

First reported in Wuhan, Hubei province, China, Covid-19 is a disease caused by severe acute respiratory disease coronavirus 2 (SARS-Cov-2) [1]. The World Health Organization (WHO) declared a global pandemic due to Covid-19 on March 11, 2020, and this disease has caused a global pandemic [2]. Approximately 660 million people were affected by this disease until December 2023 [3]. Coronavirus is a disease that can spread rapidly among living organisms and cause respiratory, liver and neurological diseases [4, 5]. Polymerase Chain Reaction (PCR) test is widely used in the diagnosis of Covid-19 [8]. However, the infection caused by Covid-19 in the lung is easily visualized by X-ray and CT imaging methods. Physicians can make a definitive diagnosis with radiologic images of patients based on these findings [9]. The workloads of healthcare personnel and especially radiologists has increased significantly with the intensity of the workloads. Computer-aided systems are needed to increase the accuracy of diagnosis and reduce the labor force to prevent errors that may occur under intense workloads. [1] These systems are systems that are active by using health and engineering disciplines together, can work under intense load, can make fast decisions, and are reliable since their error and error rates are very low. Computer-aided systems are frequently used in the literature for the diagnosis of

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Covid-19 disease. Some of the studies in this field in the literature are as follows:

Shuai Wang et al. obtained 1065 CT images from 180 typical viral pneumonia and 79 Covid-19 patients to diagnose Covid-19 disease with AI techniques. In the model they developed for image processing and classification, they trained the InceptionV3 network on the ImageNet dataset with transfer learning. The model achieved 93% accuracy in internal validation and 81% accuracy in external validation [10].

Shuo Wang et al. used 4272 CT images in their study. They designed a three-step method for automatic lung segmentation, concealment of non-study regions and Covid-19 diagnosis on CT images. They preferred DenseNet-121-FPN network for lung segmentation and achieved 87% to 88% accuracy in diagnosis. At the same time, they performed a prognostic analysis and demonstrated that the results of the DL have prognostic values [11].

Lin Li et al. included 4356 CT images from 3322 patients to detect Covid-19, pneumonia and nondisease classes with AI methods. In the deep network they named COVNet, they used a ResNet-50 based structure that can extract two- and three-dimensional features. By combining the features they obtained, they created probability values for Covid-19 patients, pneumonia and non-disease classes. The results showed 96% accuracy for Covid-19, 95% accuracy for pneumonia and 98% accuracy for non-disease classes [12].

Kassania et al. used CT images of 137 Covid-19 patients, 117 pneumonia patients and 20 healthy individuals. They extracted meaningful features using Convolutional Neural Networks (DNN) on the images. They evaluated the extracted features with different classifiers and analyzed them comparatively. The results showed that they obtained 99.00±0.09% accuracy with the DenseNet-121 network and Bagging algorithm used in feature extraction [13].

Umut et al. obtained a total of 3000 image fragments in 16x16 and 32x32 dimensions using CT images of 53 Covid-19 patients. They trained these fragments on VGG-16, GoogleNet and ResNet-50 models and combined the feature vectors obtained. The best results were obtained with ResNet-50 with 94.3% for 16x16 data and GoogleNet with 98.87% for 32x32 data. The features obtained in another method were also ranked by T-Test and trained with an SVM classifier. The results showed that 95.60% accuracy was achieved for 16x16 data and 98.27% for 32x32 data [14].

Muhammad Farooq et al. analyzed 5941 lung images of 2839 patients. The dataset was divided into 4 classes as healthy, bacterial pneumonia, non-Covid-19 viral pneumonia and Covid-19 patients. They obtained 96.23% accuracy with their proposed neural network COVID-ResNet [15].

Ying Song et al. used data from CT images of 777 Covid-19 patients, 505 bacterial pneumonia patients and 708 healthy individuals. They used a network called DRENet proposed in the study and achieved 95% accuracy. They also achieved 93% accuracy using DRENet network for bacterial pneumonia and healthy people in the dataset [16].

In this study, it aims to detect Covid-19 with a bidirectional AI approach from 1379 CT sections of 218 patients obtained from Elazig Fethi Sekin City Hospital. In the first approach, a customized proposed model and the classification process were carried out by means of the frequently used DE networks in the literature. In the second approach, the features extracted from deep networks are subjected to feature selection process and then classified with machine learning algorithms. The results of the two approaches are evaluated using performance evaluation metrics. The first section of the study covers the importance of the study and similar studies in the literature, the second section covers the dataset and the study methodology, the third section covers the experimental findings and discussion and the fourth section covers the results.

2. Material and Method

2.1. Dataset

The dataset used in the study was created from lung tomography images provided by Elazig Fethi Sekin City Hospital. The dataset includes data collected from 118 patients diagnosed with Covid-19 and 100 individuals in good health. On average, six chest tomography sections were taken from each participant. In total, 1379 tomography sections were obtained, 751 from Covid-19 patients and 628 from healthy individuals. Sample sections of healthy individuals and Covid-19 patients among these data are given in Figure 1.

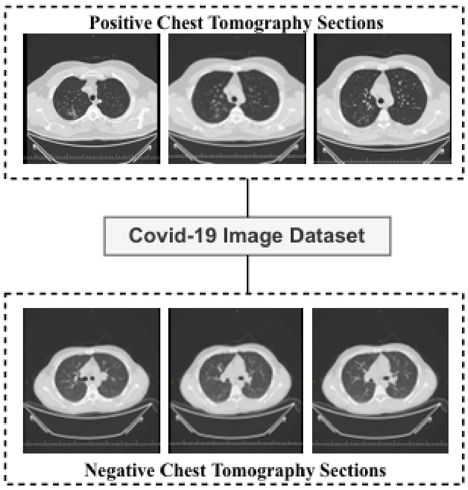

Figure 2 Sample image of the dataset

2.2. Method

The study was conducted using a total of 1379 CT slices, 751 Covid-19 and 628 healthy slices, obtained from the Elazig Fethi Sekin City Hospital. 70% of the slices (966 slices) were reserved for training and 30% (413 slices) for test set. Basically, two approaches are adopted in the proposed study. In the first approach, in addition to a proposed model, we compare the identification accuracies of the widely used DL networks in the literature. In the second approach, a hybrid methodology is proposed. Feature extraction is performed on the images obtained from the CT slices given to the DL networks, and then the most effective features are selected from the extracted features and classified with machine learning algorithms.

2.2.1 Classification with DL Networks

In this approach, AlexNet, GoogleNet, VGG-16 and VGG-19 deep learning networks that were pre-trained on ImageNet were used for classification. By adopting a transfer learning approach, the model training processes were completed by harmonizing the weights in the network layers with our dataset. In this approach, batch size, learning rate and epoch numbers were determined as 16, 1.2e-2, 50 for AlexNet, 16, 1.2e-3 for GoogleNet, 16, 1.1e-1, 50 for VGG-16 and 16, 1.1e-3 for VGG-19 respectively. In addition to the transfer learning process, a specialized DL network was proposed. The method and process design of the proposed approach is given in Figure 2.

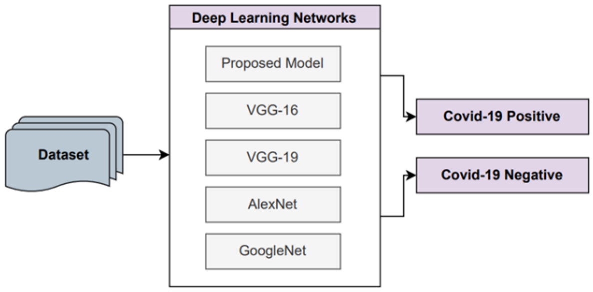

Figure 1 Classification process with deep networks

In the proposed method, the data are first converted into 2-channel gray images, resized as 100x100 and given as input to a sequential network consisting of 8 layers. The model has 5 convolution and pooling layers and 1 fully connected layer. Before the fully connected layer, there is another layer where the feature maps are converted into feature vectors and then forwarded to the fully connected layer. In the last layer of the network, the network is finalized with the classification layer. Sigmoid was used as the activation function in the fully connected layer and Rectified Linear Unit (ReLu) in the other layers. In addition, 256x256 filters were used in all layers except the fully connected layer and the output layer [17].

AlexNet was developed by Alex Krizhevsky, Ilya Sutskever and Geoffrey Hinton. In 2012, it was instrumental in making CNNs popular again. AlexNet uses ReLu as activation in non-linear parts. AlexNet has 8 layers, 5 convolutional and 3 fully connected layers. Using maximum pooling in pooling layers, AlexNet can compute approximately 60,000 parameters [18].

GoogleNet has a structurally different architecture compared to other networks. This network, also called Inception networks, consists of 9 layers of modules, each called Inception, and has a depth of 22 layers with these modules. The convolution layer, which applies a 7x7 filter in the first layer, aims to reduce the size of the images without losing spatial information. The input image size is reduced until it reaches the initialization module, but a larger number of feature maps are generated. There are two maximum pooling layers between the initial modules, which continue in sequence. After the initialization modules are finished, the network continues to the average pooling layer. Then a layer that prevents overlearning and then a linear layer are connected to the softmax layer and the network ends [19].

The VGG-16 network, which is one of the deep networks with the simplest structure, consists of 16 layers in total, including 13 convolutional and 3 fully connected layers. Approximately 128 million parameters are computed in the network. The most important difference compared to other models is that the filters of the 5 convolutional blocks in the architecture are used with 2 or 3 filters. In each convolution step, the input size is halved while the filter size is doubled. In addition, the network ends with 3 fully connected layers of different sizes, the last of which is the Softmax layer [20].

VGG-19 is a DL model defined by ReLU activation functions, consisting of 5 convolutional block layers and 16 convolutional layers terminating in 3 fully connected layers. In this network, which consists of 24 main layers in total, the filters are 3x3 in size and are used to reduce the number of parameters. The VGG-19 network contains more parameters (138 million) compared to the VGG-16 network in parallel with its approximate number of layers [21].

2.2.2 Classification with Hybrid Method

In this approach, firstly, CT images in the dataset are given as input to VGG-16, VGG-19, DenseNet-121, ResNet-50 and MobileNet networks that are pre-trained with ImageNet by adopting a transfer learning approach. Before the fully connected layer of each network, the best 1000 features were selected from the features obtained from CT images by PCA technique. RO and SVM classifiers were used to classify these features. The process design of this approach is given in Figure 3.

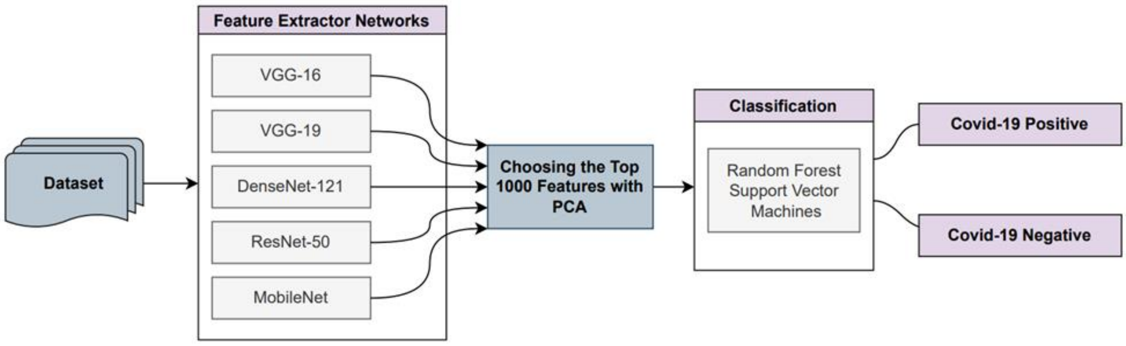

Figure 3 Classification process with hybrid method

Feature Extraction with DL

In the first two steps of this approach, 25,088 features were first generated from the fully connected layers of the VGG-19 and VGG-16 networks. These features were made ready to be used in the next step.

DenseNet networks were proposed by Huang et al [22]. DenseNet networks basically aim to incorporate the features generated in each layer into other layers without losing them. The aim here is to reuse the generated features without increasing the number of parameters and not to lose them. The basic structure of DenseNet networks consists of blocks called Dense [23]. There are many types of DenseNet networks. In this study, the DenseNet-121 network with a depth of 121 layers was used. The data to be given as input to the DenseNet-121 network should be 3-channel and no smaller than 32x32 according to the limitations accepted by the model. By default, the network receives 224x224x3 data as input. In our study, size transformations were applied on the data according to the input dimensions accepted by each network and the data were used in these dimensions. Then, before the fully connected layer, 50,176 features obtained from the data were made ready to be used in the next step.

In convolutional networks, as the depth of the network increases, its performance decreases. This is because the information between layers is corrupted and cannot be transmitted to the next layer. ResNet adds shortcuts between layers to solve this problem [24]. There are variants of ResNet with 34, 50, 101 and 152 layers. In this study, the ResNet-50 model with a depth of 50 layers is used. The data to be given as input to the ResNet-50 network must be 3-channel, like the DenseNet network. In ResNet-50 network, data are commonly given as input to the network in 224x224 dimensions. In our study, these dimensions were used in the network. Then, before the fully connected layer, 100,352 features obtained from the data were made ready to be used in the next step.

MobileNet, the CNN model proposed in 2017, basically consists of 28 layers. Since MobileNet is developed for mobile and embedded applications, it requires little processing power and provides high performance. The MobileNet approach minimizes the model size and reduces power and time costs [25]. MobileNet takes at least 32x32 dimensions of data as input. The network commonly accepts 224x224x3 data as input. In our study, data is given to the network as input in the accepted dimensions. Then, before the fully connected layer, 50,176 features obtained from the data were made ready to be used in the next step.

Feature Selection with PCA

PCA is a statistical technique used to maximize variance in data and reduce dimensionality. It allows to reduce the data set to smaller dimensions by analyzing the correlations between observations in multidimensional data sets. It is frequently used to find and visualize hidden structures, especially in large data. PCA consists of the following basic stages:

Standardization: Each feature in a data set is scaled so that its mean is zero and its variance is one. This step ensures a fair comparison of features with various scales.

Covariance Matrix Calculation: This process is used to calculate the covariance matrix of the standardized data. The covariance matrix shows the linear relationships between the features. Eigenvalues and eigenvectors of the covariance matrix are calculated. Eigenvalues express the variance of each principal component in the data set, while eigenvectors determine the direction of these components.

Ranking of Eigenvectors: Eigenvectors with the highest eigenvalues are the principal components that show the most change in the data set. Eigenvalues are ranked from largest to smallest.

Transformation: The original data matrix is transformed into a new space using the selected eigenvectors. This procedure creates a new dimensionally reduced data set [26].Below is the pseudo code explaining the steps of the PCA algorithm [27].

Algorithm PCA Algorithm Pseudocode

```
Input
A: Data matrix of dimensions m x k (m samples, k features)
d: Target number of dimensions (d <= k)
Standardize
For each column (j = 1 to k):
    μ_j = Calculate mean(A [:, j])
    σ_j = Calculate standard deviation(A [:, j])
    for i from 1 to m:
        A [i, j] = (A [i, j] - μ_j) / σ_j

Calculate the Covariance Matrix
CM = (1/n) * A^T * A
Calculate Eigenvalues and Eigenvectors
B, X = Find eigenvalues and eigenvectors(CM)
If B and X are in matrix form, the columns of X are the eigenvectors
Select the Largest d Eigenvalues
Sort indices(B)
Selected_eigenvectors = first d eigenvectors
Transform
New data matrix Y = A * Selected_eigenvectors
Output:
Y: Data matrix of dimensions m x d
```

In this study the correlation between variables was examined by using the PCA method on the features obtained from feature extraction for each model and the most significant 1000 features were selected. These features were then passed as input to the classifiers.

Classification

In this study, RF and SVM classifiers are used to classify the best 1000 features obtained by PCA. The RF classifier is basically a method based on decision trees. This is seen as a problem since decision trees overfit the data used. To overcome this problem, the RF classifier randomly divides the data into dozens of subsets and eliminates the overfitting problem by training these subsets separately. As a result of this training, predictions are obtained from different decision trees. Among these predictions, the trees with the highest accuracy and independence are combined together to make the prediction [28]. In this study, the number of trees for the RF classifier is set to 100. Gini algorithm was used to measure the splitting quality of the trees.

SVM can solve regression and classification problems and is based on statistical learning theory. It can work on linearly separable and non-linearly separable data. SVM basically finds the most appropriate hyperplane that can separate these classes in a data set divided into 2 classes. The data on this plane are called support vectors. While finding this plane, it estimates the most appropriate decision function that can separate the data. To estimate the decision function in the best way, it is necessary to find a linear and realistic function for each data in the training data [29].

3. Experimental Results and Discussion

A total of 1379 CT slices were used as the dataset in the study. In the first approach, these data were classified using a proposed model and well-known networks trained with large image data. In the second approach, the features of the data were extracted with deep networks trained with large image data, these features were selected by PCA and these selected features were given as input to the classifiers. The results of the classifiers were evaluated with the metrics of Specificity, Sensitivity, F1-Score and Accuracy. The descriptions of the evaluation metrics are given in Figure 4 and their calculations are given in Equations 1-4.”

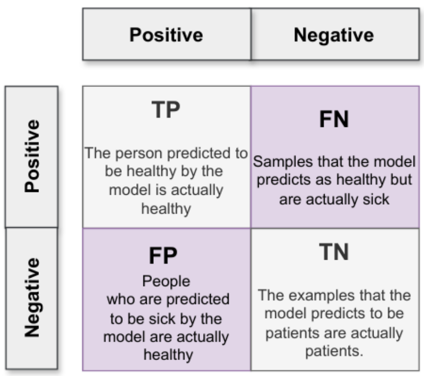

Figure 4 Performance evaluation metrics

The calculations of the performance evaluation metrics obtained by using the values in Figure 4 are given in Equations 1-4.

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

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

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

$$F1\ Score = \frac{2*TP}{2*TP\ /\ (2*TP+FP+FN)} \quad (4)$$

In the developed application, Covid-19 disease was approached as a classification problem using lung images and a solution to this problem was sought. In the first proposed approach, the classification was performed with the DL networks and the network we proposed reached 95.61% accuracy. Apart from this, classification accuracy was 80.39% with AlexNet, 93.90% with GoogleNet, 93.75% with VGG-16 and 88.38% with VGG-19. Considering the achievements and other results it is seen that the performance of the proposed model is better than the other models. In the second approach, in the first step, features were extracted from the dataset with 5 DL networks. These features were selected with PCA and classified with RF and SVM classifiers. As a result of this classification, 93.94% accuracy was obtained when the features obtained from VGG-16 and MobileNet networks were classified with SVM. When the performance metrics such as Sensitivity, Specificity, F1-Score are analyzed together, the method in which the features obtained from MobileNet network are classified with SVM comes to the forefront. The performance metrics of the results of the proposed approaches are given in Figure 5. The first graph in Figure 5 presents the performance of the overall classifiers, while the second graph details the performance of the feature extraction networks combined with different classifiers.

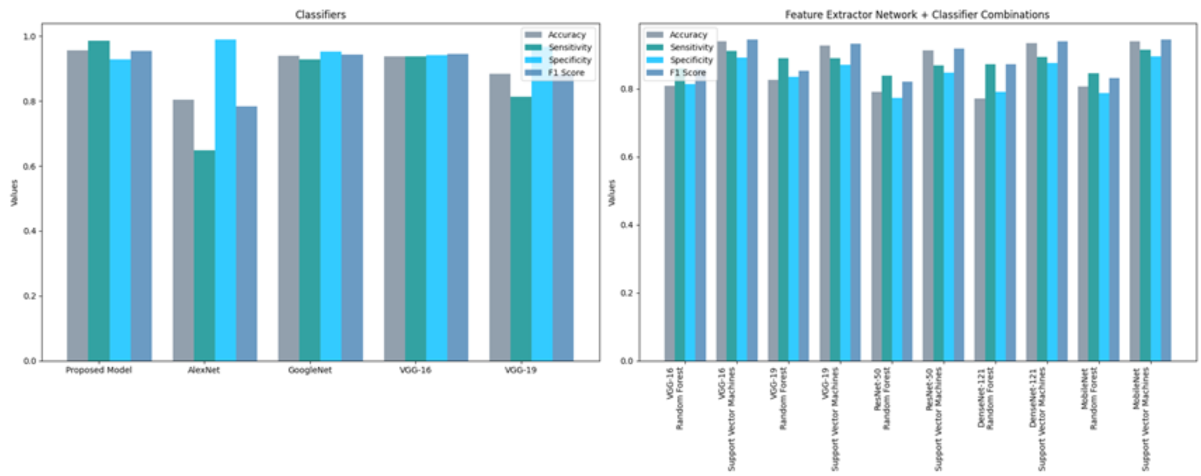

Figure 5 Performance comparison of different DL models and classifier combination

The complexity matrices from which the evaluation metrics of the best performing methods in both approaches in Figure 5 are obtained are given in Figure 6.

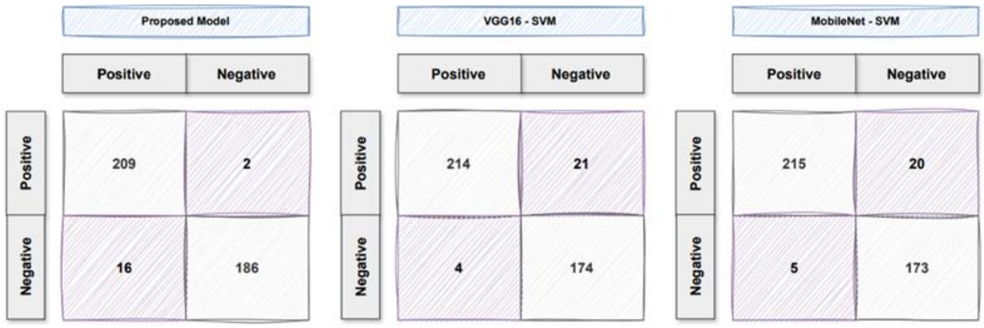

Figure 6 Complexity matrices for the study

In the proposed study, it aims to perform the diagnosis of Covid-19 disease with two different AI approaches by using the data on Covid-19 and healthy patients obtained from Elazig Fethi Sekin City Hospital. Two different approaches were proposed and customized techniques were used on the dataset. In the first approach, the classification of Covid-19 and healthy data was performed with the transfer learning method and the customized network proposed in addition to it, while in the second approach, feature selection was performed on the features obtained from deep networks and classification was performed with machine learning algorithms. When the results of the two approaches are analyzed mutually, it is observed that the highest accuracy is achieved with the proposed network in the first approach. When analyzed with the studies in the literature mentioned in the introduction, the proposed approaches have strong and weak points. Some of these studies are given in Table 1 in comparison with the proposed approaches.

Table 1 Studies in the literature

Number	Authors	Year	Data Set/Dimension	Methods	Accuracy (%)
1	Shuai Wang et al. [10]	2021	CT Images/299 x 299	InceptionV3	93
2	Shuo Wang et al. [11]	2020	CT Images/-	DenseNet-121-FPN and COVID-19Net	99
3	Lin Li et al. [12]	2020	CT Images/224 x 224	U-Net and COVNet	96
4	Sara Hosseinzadeh Kassania et al. [13]	2021	Radiography Images and CT Images/600 x 450	8 DL Networks and 6 Classifier	99
5	Umut Özkaya et al. [14]	2020	CT Images/16x16 and 32x32	3 DL Network, T-Test and SVM	98,2

6	Muhammad Farooq et al. [15]	2020	Radiography Images/128x128, 224x224, and 229x229	COVID-ResNet	96,2
7	Ying Song et al. [16]	2021	CT Images/512 x 512	4 DL Networks	93
8	Omneya Attallah [30]	2023	CT and Xray/119 x 104 to 416 x 512	3 DL Networks	99,4
9	Ahmad Imwafak Alaiad et al. [31]	2023	CT Images/224x224	8 DL Networks	99,5
10	Proposed Study	2024	CT Images/1280 x 554	5 DL Networks	95,6
				5 DL Networks, PCA and 2 Classifier	93,9

4. Conclusion

In this study, it aims to develop an auxiliary decision support system for the diagnosis of Covid-19 disease on CT data using DS techniques. Within the scope of the study, two different approaches were proposed and these approaches were evaluated comparatively. In the first approach, the features extracted by the deep networks from the data were transmitted to the fully connected layer and classification was performed with all these features. In the second approach, the features extracted by the deep networks were reduced to 1000 features by PCA and included in the classification process. When the success metrics for both approaches are analyzed, it is observed that the second approach achieves high success rates with fewer features. Considering the gains of the study such as not requiring significant labor and resources for the healthcare sector, it has been observed that it can be considered as an auxiliary resource for healthcare professionals in the diagnosis of Covid-19.

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