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A hybrid CNN–KNN approach for identification of COVID-19 with 5-fold cross validation

Zarin Anjuman Sejuti, Md Saiful Islam *

Department of Electronics & Telecommunication Engineering, Chittagong University of Engineering & Technology, Chattogram, Bangladesh

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ABSTRACT

The novel coronavirus is the new member of the SARS family, which can cause mild to severe infection in the lungs and other vital organs like the heart, kidney and liver. For detecting COVID-19 from images, traditional ANN can be employed. This method begins by extracting the features and then feeding the features into a suitable classifier. The classification rate is not so high as feature extraction is dependent on the experimenters' expertise. To solve this drawback, a hybrid CNN–KNN-based model with 5-fold cross-validation is proposed to classify covid-19 or non-covid19 from CT scans of patients. At first, some pre-processing steps like contrast enhancement, median filtering, data augmentation, and image resizing are performed. Secondly, the entire dataset is divided into five equal sections or folds for training and testing. By doing 5-fold cross-validation, the generalization of the dataset is ensured and the overfitting of the network is prevented. The proposed CNN model consists of four convolutional layers, four max-pooling layers, and two fully connected layers combined with 23 layers. The CNN architecture is used as a feature extractor in this case. The features are taken from the CNN model's fourth convolutional layer and finally, the features are classified using K Nearest Neighbor rather than softmax for better accuracy. The proposed method is conducted over an augmented dataset of 4085 CT scan images. The average accuracy, precision, recall and F1 score of the proposed method after performing a 5-fold cross-validation is 98.26%, 99.42%,97.2% and 98.19%, respectively. The proposed method's accuracy is comparable with the existing works described further, where the state of the art and the custom CNN models were used. Hence, this proposed method can diagnose the COVID-19 patients with higher efficiency.

1. Introduction

The novel Coronavirus, which causes respiratory tract illness in humans, is also known as Coronavirus disease, COVID-19. It can be transferred to the people by droplets released by coughing, sneezing, or speaking to infected persons. Someone may become infected with items in the virus and then contact the eyes, mouth and nose [1]. The first COVID-19 infected patient was identified in China's city of Wuhan in the middle of November 2019 and has received a WHO-announced public health emergency [2,3]. It has spread widely due to not maintaining proper social distance and having less immunity against this virus [2]. Until 22 August 212, 409, 713 confirmed cases of Covid-19 and 4,441, 800 death reports are counted [4]. A fruitful screening of covid-19 can be achieved by chest's Computed Tomography scan. Mainly CT scan is a combination of a sequential X-Ray images which are captured from several directions of our body [5]. CT scans generate detailed images of various organs, blood vessels, bones, and soft tissues, allowing doctors to examine their internal anatomy [3–6]. CT scans can offer a more accurate and specific image of the patient's state than normal x-rays. This specific knowledge will be used to assess the nature and precise location of a medical condition. Due to the scarcity of COVID-19 kits and the rush in hospitals for RT-PCR tests, a fast, automatic process of identifying this virus needs to be developed to prevent its spreading [6]. Besides, the RT-PCR test requires much time to give the result. Research on 1014 patients of Wuhan, China, underneath COVID CT images and investigated the constancy of chest computed tomography with the contrast of

* Corresponding author.
E-mail addresses: zarinanjumansejuti08@gmail.com (Z.A. Sejuti), saiful05eee@cuet.ac.bd (M.S. Islam).

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RT-PCR is shown [7]. The RT-PCR was employed as a reference, and the performance of CT testing was carried out for a protracted month. From 1014 patients, 601 (59%) were tested positive in the RT-PCR test, and 888 (88%) were tested positive in Chest CT. Chest CT sensitivity is 97%, which may be considered the primary diagnostic tool of COVID-19 based on the RT-PCR test. Researchers say that COVID-19 can be helped by incorporating the clinical imaging characteristics with laboratory results more quickly [8,9]. Automated detection with an in-depth knowledge of this disease can be the best method. For these reasons, several deep learning approaches have been recommended for COVID-19 detection in CT images. Deep learning is a sub-set that enables computers to teach raw dataset characteristics Deep learning [10]. It is an artificial intelligence research field that develops end-to-end models that can generate amazing results from input pictures or data without manual function extraction [11,12].

Cai [13] has combined two publicly available datasets [14,15] and trained them on ResNet architecture. Instead of having a decent number of images in the dataset, it shows an accuracy of 94.3%. The proposed method in Refs. [3,17] has achieved a higher accuracy, but it may not be implemented on memory restricted devices because of its huge number of parameters. To tackle these problems, it is proposed to use a 5-fold cross-validation automated Hybrid CNN–KNN technique that can grade COVID-19 patients using CT images. Here, multiple layered CNN is designed for feature extraction, and a well-known classifier, K-nearest neighbor is applied to classify the CNN features. An automated algorithm like CNN as a feature extraction can be used because it can produce deep learned features that can further be used on proven classifiers and a comprehensive evaluation. The importance of the neural networks of convolution is the combination of several layers, which have a number of neurons. These neurons are deeply connected between layers and perform weight sharing. Significant contributions of this paper are.

- A deep learning-based identification method of COVID-19 from computed tomography scan images is proposed by combining two different algorithms CNN and KNN
- To improve the performance of the deep convolutional neural network, data augmentation is applied, which increases the dataset's number of images.
- A basic CNN model is developed with fewer parameters, as opposed to a pretrained network, which is applicable for mobile device.

2. Background studies

Zheng [18] has proposed a software framework to identify COVID-19 patients from 3-D CT scans using the deep learning concept. Here for segmentation and training, the dataset pre-trained UNet [19] and 3-D CNN network named DeCoVNet are used, respectively. This deep CNN model is split into 3 stages (network stem, 3D residual blocks, progressive classifier). After preprocessing steps, data augmentation is conducted to prevent overfitting of the model. The overall accuracy of this system is 90.8%. In Ref. [20], for detection of COVID-19, a deep neural network named as DeepPneumonia is designed and implemented on a chest CT scan dataset collected from different hospitals. The methodology of the proposed system is divided into 3 major steps. Initially, the lung portion of the CT images are extracted. Secondly, image-level predictions are acquired from the extraction of top-k formation in images by designing DRE-Net. Lastly, diagnosis of patient-level is executed and, classification accuracy, in this case, is 86%. In Ref. [21], Ioannis developed a technique based on transfer learning to distinguish positive and negative COVID patients from chest X-ray pictures. Several pretrained architectures like Mobile Net [22], Xception [23], VGG19 [23], Inception and Inception ResNet v2 are trained over a dataset containing a total of 1427 images, including COVID-19, pneumonia and normal patients. Batch size and the number of epochs is chosen 64 and 10, respectively, as training hyper-parameters. The best accuracy of 98.75% and 97.40% are gained from VGG19 And MobileNetV2 for two class classifications consecutively, but

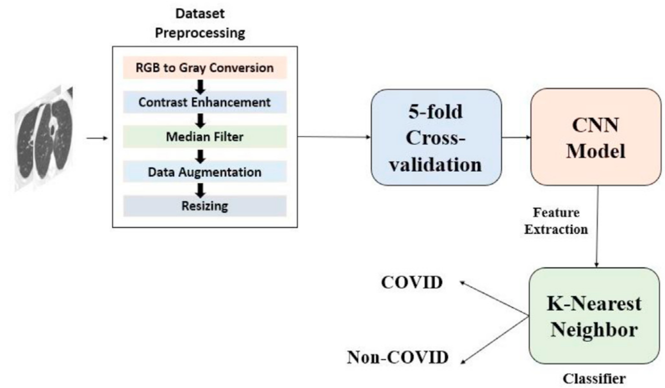

Fig. 1. Working procedure of the proposed hybrid system.

the proposed method's overall accuracy is 97.82%. Heidari [25] has analyzed the CNN performance by applying some preprocessing algorithms for COVID19 detection. A key contribution of this proposed method is in preprocessing steps. The diaphragm portion of chest x-ray images is omitted by thresholding, converting to binary images, applying morphological filters and bilateral low-pass filter consecutively. A pre-trained VGG-16 model is used to experiment with the method over 8474 chest x-ray images. Final accuracy is 94.5% on average. Ozturk has proposed a DarkCovidNet model comprised of 17 convolutional layers for COVID-19 detection [26]. The dataset includes 127 Covid positive cases of chest x-ray images. Each "DarkNet" block is designed with one convolutional 2D layer, one batch-normalization layer and a leaky rectified linear activation function layer. Pooling layers, fully-connected layers and flatten layer are also applied to establish the proposed model. The corresponding accuracy for two class and triple class classification is 98.08% and 87.02%. In Ref. [16], three experiments are conducted over three types of datasets [14,27,28] to detect COVID-19. They have modified the VGG-19 network with extra 5 layers with a total of 20, 548, 866 parameters. The highest accuracy (95.61%) was obtained for the dataset [28]. In other words, a patient with a Pneumonia diagnosis is more likely to be examined as a false positive. The grade-CAM, a color visualization approach, is also used to make the suggested method more explicable. The classification performance of four CNN architectures via transfer learning are investigated in Ref. [29]. In this study, ResNet-50 is found to be the most effective architecture using 3993 CT images, although general accuracy is attained at rates that ranged from 0.626 to 0.995. A categorization study has employed ResNet based convolutional neural networks) and Noisy or Bayesian Function techniques in Ref. [30]. The study has used 618 CT images, and the accuracy rate is determined to be 0.867.

The researchers have used several transfer learning approaches like UNet, MobileNet, Xception, VGG-19, Inception, MobileNetV2 and also, proposed some custom CNN models like DeCoVNet, DarkCovidNet, DRE-Net. Among the above researches, the highest accuracy of 98.08% is obtained for two class classifications in Ref. [26] using a custom-CNN model (DarkCovidNet).

3. Dataset

The dataset consists of SARS-CoV-2 CT scan images with 2482 CT scans. These CT images have been collected from different Sao Paulo, Brazil hospitals. Of the 2482 pictures, 1252 images are from covid positive patients, including 32 males and 28 females and 1230 images are from covid negative patients including, both 30 males and females shown in Table .2. In this dataset, no standard size for CT scan images is maintained. Also, all image's contrast is not the same. The dataset is available at Kaggle [31] and used in a method [3]. It is compiled by Soares [14], and is accessible publicly.

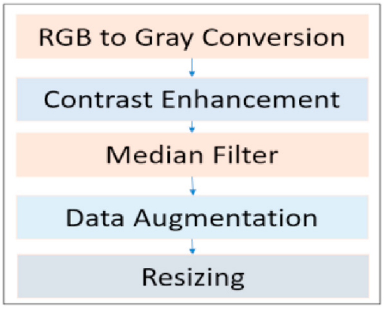

Fig. 2. Preprocessing steps.

4. Methodology

This paper proposes a hybrid CNN–KNN method to identify COVID-19 positive and negative patients from CT scan. The working procedure for the proposed hybrid system is shown in Fig. 1.

Deep learning is a subfield of machine learning that is inspired by brain structure. Deep learning approaches that have been deployed in recent years continue to perform admirably in the field of medical image processing, as well as. And many other sectors. CNN architecture can automatically and efficiently extract features. The extracted features are then classified using KNN, which improves the overall accuracy.

The proposed system methodology can be subdivided into five steps are discussed below.

4.1. Preprocessing

Preprocessing is a well-known technique in the area of computer vision. The objective of the preprocessing is to get an improved version of an image from a raw image. Several preprocessing steps are applied to the original SARS-CoV-2 CT-scan dataset, which is shown in Fig. 2.

I. RGB to gray conversion

The images obtained from the dataset are in RGB format. So, they are converted to gray images at first in Fig. 3(b). The algorithm is simplified by grayscale and minimizes the time it takes to complete.

II. Contrast Enhancement

After the gray conversion, contrast enhancement is done to adjust the contrast of the images since the images of the dataset are of different contrast (Fig. 3(c)).

III. Median Filter

To eliminate noise from the images, the median filter is employed. The technique is carried out with a window that slides over an image. It replaces the center pixel of an N*N neighborhood with the median value of the associated window. This filter helps to smooth the image and hence significantly reduces the noise shown in Fig. 3(d). Preprocessed images of different stages are shown in Fig. 3.

IV. Data Augmentation

Data augmentation is a process where number of training images is increased by applying the augmentation technique to the original image [3]. Basically, it generates variations of the actual image. In order to train the convolutional neural network, the role of data augmentation is crucial [32]. Expanding the original dataset, data augmentation is done, which helps the proposed model perform better. Also, it prevents the overfitting problem of the model. Before training the proposed model, four types of data augmentation methods are applied to the original dataset [4]. These techniques are flipping, reflection, scaling and shearing of the original image dataset. The vertical flip strategy is applied on 201 images from the Covid-19 class and 200 images from the non-covid-19 class. For shearing, an image x-shear strategy is used as shear means the distortion of an image along the axis. The amount of

Table 1
Dataset used to implement the proposed CNN–KNN method.

Data types	Number of classes
Covid	1252
Non-covid	1230
Total	**2482**

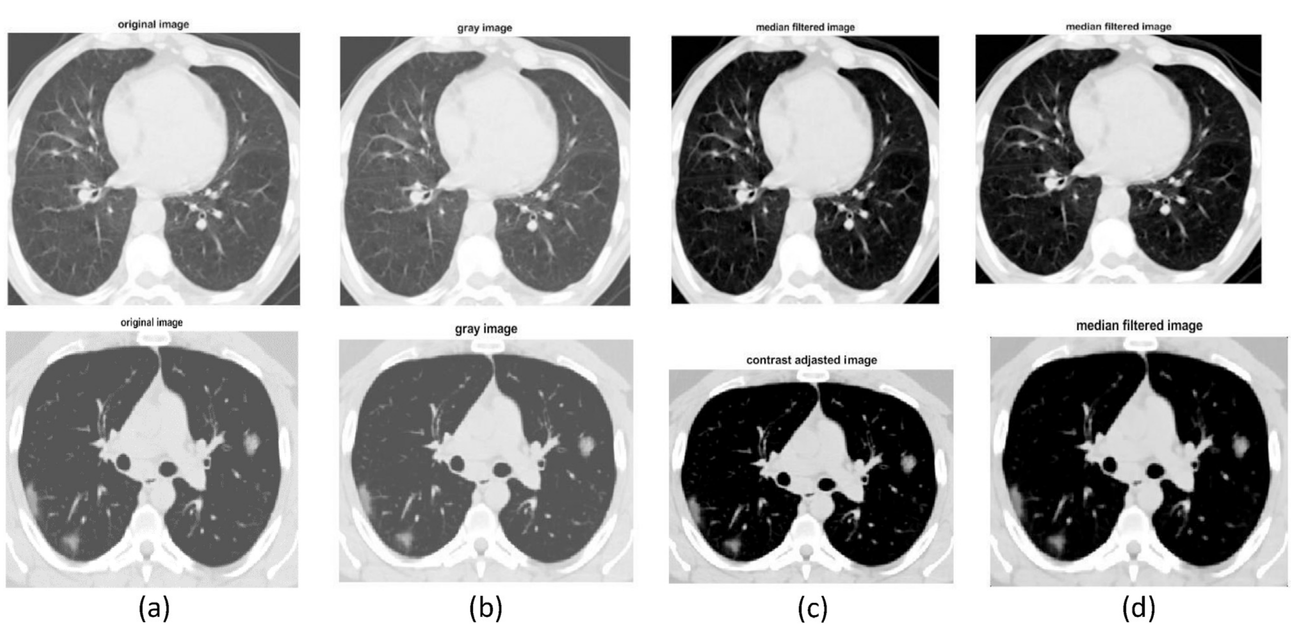

Fig. 3. Examples of non-covid and covid CT scan images where the 1st row images are non-covid and 2nd row are covid images. The figure also shows (a) raw input image, (b) gray image, (c) contrast-enhanced image and (d) median filtered image.

Table 2
Dataset description after applying augmentation technique.

Class	Number of Original Images	Augmentation Technique				Number of Augmented Images
		Reflection	Scaling	Flipping	Shearing	
COVID-19	1252	203	200	201	200	804
NON COVID-19	1230	200	200	200	200	800
Total	**2482**	**403**	**400**	**401**	**400**	**1604**

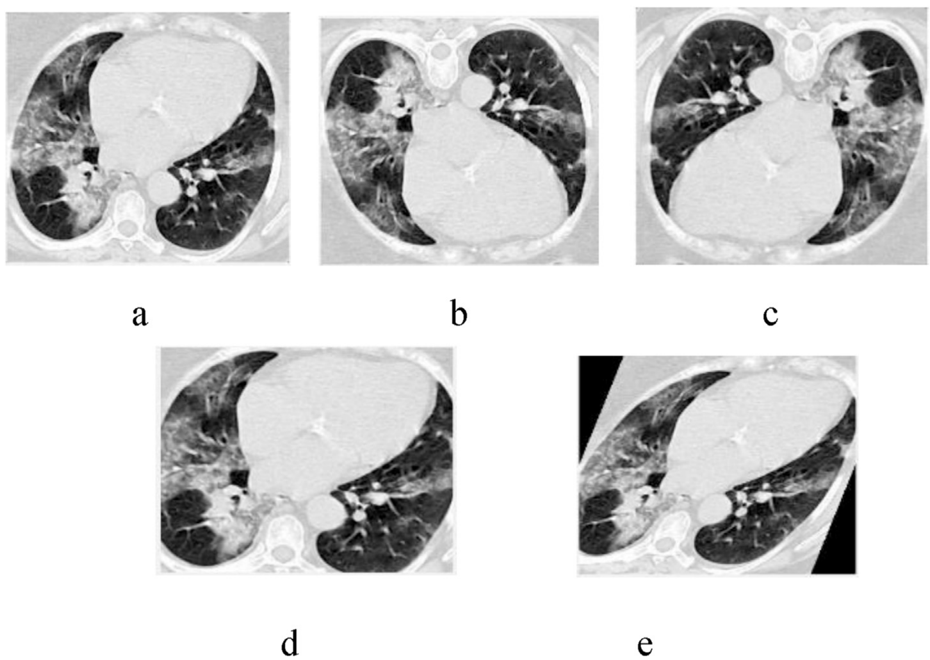

Fig. 4. Augmented images of original dataset (a) original CT scan of a COVID-19 patient (b) flipped CT scan of a COVID-19 patient (c) rotated CT scan of a COVID-19 patient (d) scaled CT scan of a COVID-19 patient (e) sheared CT scan of a COVID-19 patient.

shearing is defined by s and the range of s is 30°. The dataset details after adopting the data augmentation technique is given in Table .1 and some sample augmented images are stated in Fig. 4.

The SARS-CoV-2 CT-scan dataset is comprised of 2482 CT scans. To increase the number of samples, augmentation strategy is adopted and 4086 images are achieved from data augmentation, where 804 images belong to the covid-19 class and 800 images belong to the non-covid-19 class.

V. Resizing

At last, as the images from the original dataset are of different sizes, they are resized into the same pixels. In this case, the dimensions of the input images are kept 64*64 pixel.

4.2. Splitting dataset using 5-fold cross-validation

In 5-fold cross-validation, the entire dataset is used for part-to-part training and validation rather than randomly splitting the dataset. The original dataset comprises 2482 images and the augmented dataset consists of 4086 images. These 4086 images are divided into 5 equal parts. This means each part contains 817 images and this process is repeated 5 times, known as folding. In the first fold, first part, including 817 images is used for validation and the remaining for training. Similarly, in second fold, the 2nd part is used for validation. This process is continued for the rest of the folding, which is shown in Fig. 5. Thus, by folding the dataset, overfitting of the model is prevented. As the training process is done every time with different training sets, the training process doesn't get biased towards training data. Thus, the problem of overfitting is prevented.

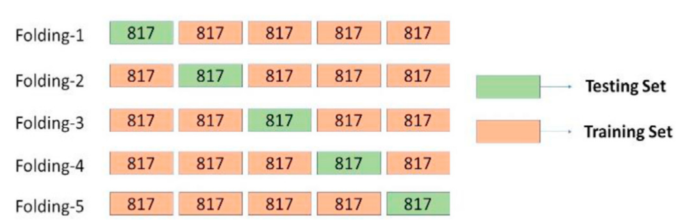

Fig. 5. Dataset splitting with 5-fold cross-validation.

4.3. Proposed CNN architecture

For the detection of COVID-19 patients from CT scans, a unique hybrid CNN–KNN model is suggested. A CNN architecture comprising 23 layers is designed including four convolutional layers, four max-pooling layers, one dropout layer, two fully connected layers and a softmax layer as a classifier. Fig. 6 represents the final model of the CNN model. Processed augmented image is fed into CNN network as an input. Both the length and width of the input images are 64. In the first convolutional layer, 5*5 kernel and 16 channels are applied to input images, which produces feature maps. To locate the important features, the filters traverse throughout the entire image [33]. The formula for the output feature map produced from convolutional layer is

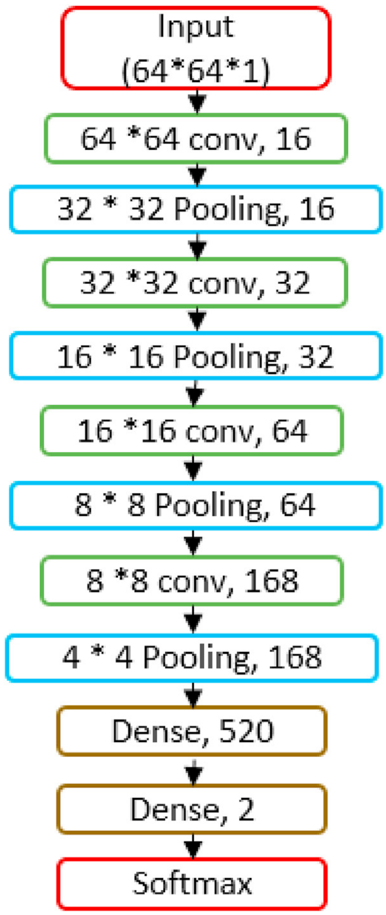

Fig. 6. Proposed architecture of CNN.

$$M_x^L = B_x^L + \sum_{y=1}^{N^{L-1}} F_{x,y}^L * M_y^{L-1} \tag{1}$$

Where M_x^L defines the output feature map, L denotes the layer, F_x, indicates the filter, number of filters are symbolized by N^{L-1}, B_x^L represents a bias and M_y^{L-1} represents input map. The detailed information of features in image is stored by these feature maps. So, in the initial convolutional layer, 64*64 input image is convolving with a number of 16 filters. After every convolution layer, a batch normalization layer and reLu activation layer have utilized. In Fig. 4, one convolutional layer, one batch normalization layer and one reLu layer are represented within a block named CN. Here, reLu layers are used as activation functions that gradually improve the non-linearity of the image. A max-pool layer of kernel size 2*2 is followed after each convolutional block which down samples the feature maps obtained from convolutional layers. By reducing the number of parameters, it lowers the cost of computing [34]. It also summarizes the features arises from a part of the feature map generated by the convolutional layer. The calculation of convolution for a single pixel from the previous layer to the next layer is given below [35]:

$$N(x,y) = (i^*w)[x,y] = \sum_m \sum_n i[m,n]\ w\ [x-m, y-n] \tag{2}$$

Here next layer output is defined by N (a, b), i is input image and K denotes kernel. The convolution operation is represented with the symbol '*'. In the second convolutional layer, 5*5 kernel and 32 channels are passed through the output of the first max-pool layer. Similarly, 3*3 filter size is specified for third and fourth convolutional 2D layers having 64 and 168 channels, respectively. The filter size and number for each convolutional layer is given in Table .3.

Table 3
Filter specification for convolutional layers.

Convolutional layers	Number of Filter	Filter Size
Convo_1	16	5*5
Convo_2	32	5*5
Convo_3	64	3*3
Convo_4	168	3*3

Table 4
Total number of parameters.

Layers	Activation Shape	Learnable Parameters
conv_1	64x64x16	416
batchnorm_1	64x64x16	64
relu_1	64x64x16	0
maxpool_1	32x32x16	0
conv_2	32x32x32	12,832
batchnorm_2	32x32x32	128
relu_2	32x32x32	0
maxpool_2	16x16x32	0
conv_3	16x16x64	18,496
batchnorm_3	16x16x64	256
relu_3	16x16x64	0
maxpool_3	8 × 8 × 64	0
conv_4	8 × 8 × 168	96,936
batchnorm_4	8 × 8 × 168	672
relu_4	8 × 8 × 168	0
maxpool_4	4 × 4 × 168	0
fc_1	1 × 1 × 520	1,398,280
fc_2	1 × 1 × 2	1042
total		**1,529,122**

The fully connected layer has two hidden layers of 520 neurons and 2 neurons are connected with the last max-pool layer via a flattening layer. In last fully connected layer, 2 neurons are chosen for classifying the COVID-19 and normal patients. In order to regularize the model, a dropout layer having a 0.5 dropout factor is applied between two fully connected layers.

Lastly, softmax layer is used for predicting classes as the probability prediction of the existing classes can be done by it. Table .1 Shows the learnable parameters required in different layers of the CNN model. Deep features for identifying COVID-19 are taken out from custom-designed CNN model. The activations of the layers of the proposed CNN model show a simple representation of images because when the layer gets deeper, the representation gets complicated. The activation summarizes the features that are important in COVID CT scan image classification. The feature maps obtained from each convolutional layer are given in Fig. 7. In Fig. 7. (a) The low-level features of the first convolutional layer having the weight of 16 are shown. In the figure, the feature maps are mainly local features like edges or corners and shapes. In Fig. 7(d), the high level feature map of the deeper fourth convolutional layer is shown. These features are then fed into the K-nearest neighbor classifier.

4.4. Parameters for CNN model

Convolutional layers and FC (fully connected) layers offer learnable parameters. The weights learned throughout CNN model training are called parameter. The formula for calculating parameters (Pconv) for convolutional layer can be evaluated as:

$$P_{conv} = F_h{}^*F_w{}^*F_{num}{}^*C_{in} + F_{num} \tag{3}$$

Filter height and width are represented by F_h and F_w, respectively. The number of filters is denoted by F_{num}. The input channel number for the corresponding layer is denoted by C_{in}. Fully connected layer parameters (P_{FC}) can be expressed as:

$$P_{FC} = A_{(prev)}{}^*N_{(unit)} + N_{(unit)} \tag{4}$$

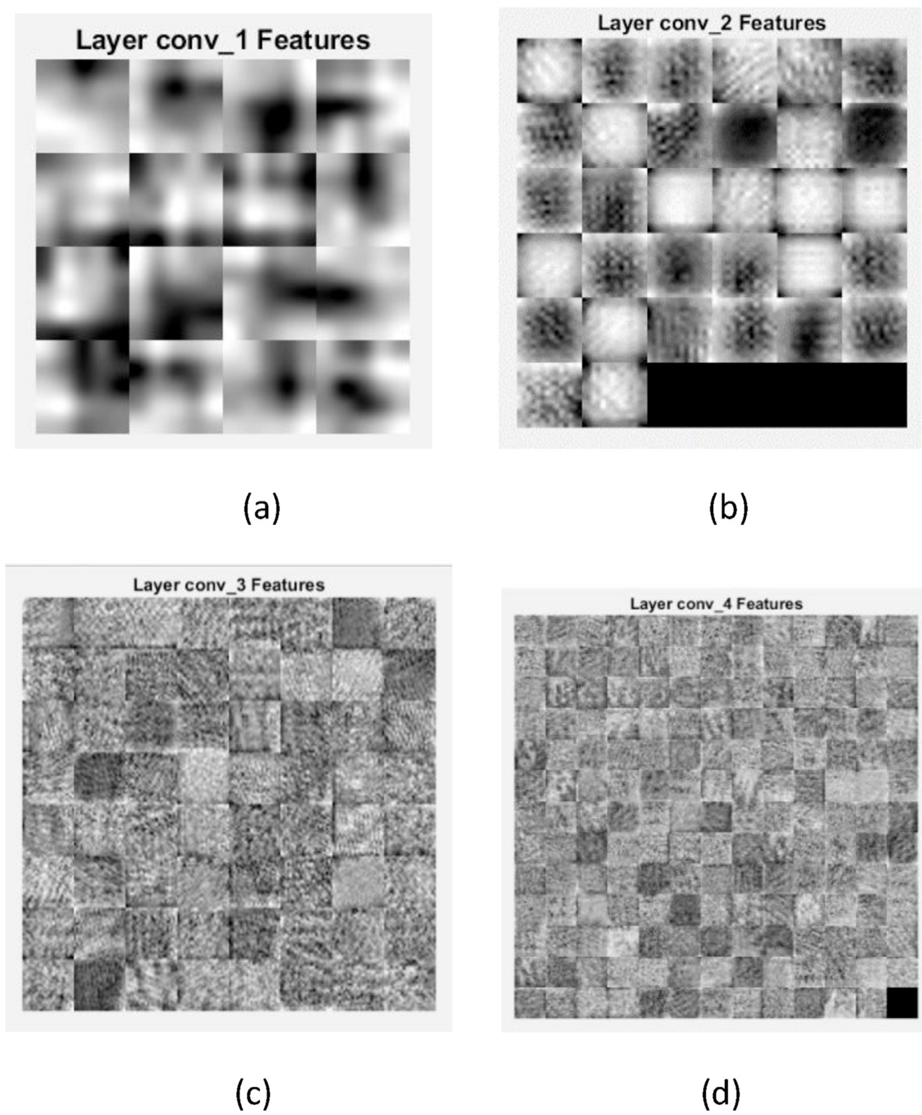

Fig. 7. Feature map of convolutional layers (a) feature map of conv_1 layer (b) feature map of conv_2 (c) feature map of conv_3 and feature map of conv_4.

Where previous layer activation shape(dimension) is represented by $A_{(prev)}$ and number of units or neurons which are presented in the current fully connected layer is represented by $N_{(unit)}$. The maxpool layer owns no learnable parameters. Parameters for the batch-normalization layer are the multiplication of the amounts of channels used in the previous convolutional layer with four.

Here the total parameters are 1,530,242, where the number of the learnable parameters is 1,529,122, and the number of the non-learnable parameters is 1120.

4.5. *Classifiers*

I. Softmax

A softmax activation function is used in CNN after the fully connected layers. The equation of this activation function can be defined as:

$$Softmax(a_i) = \frac{e^{a_i}}{\sum_{j=1}^{n} a_j} \tag{5}$$

Here, a is the set of n number of variables. The softmax activation function converts the output into probability measure. This activation function uses a cross-entropy loss function and the training process of CNN is driven by this. The equation of cross-entropy loss function:

$$L_f = -\sum_i x^i \log x_i^{'} \tag{6}$$

Where L_f represents the cross-entropy loss function. x and x' symbolize the real and predicted value of output, respectively. The loss is low when the accurate and the predicted value is closer to each other. Cross-entropy loss function measures how close the actual and predicted values are and this is important for training and the calculation of the gradient, specially, in back propagation. But when the incorrect prediction occurs, the mean square error receives a penalty heavily. For this reason, MSE is not suitable for probabilistic output.

II. K Nearest Neighbor

In the KNN classifier, the Euclidian method uses the root of the sum of the features to calculate the distance between two points of any system. The formula of the Euclidian distance method is written below:

$$R = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2} \tag{7}$$

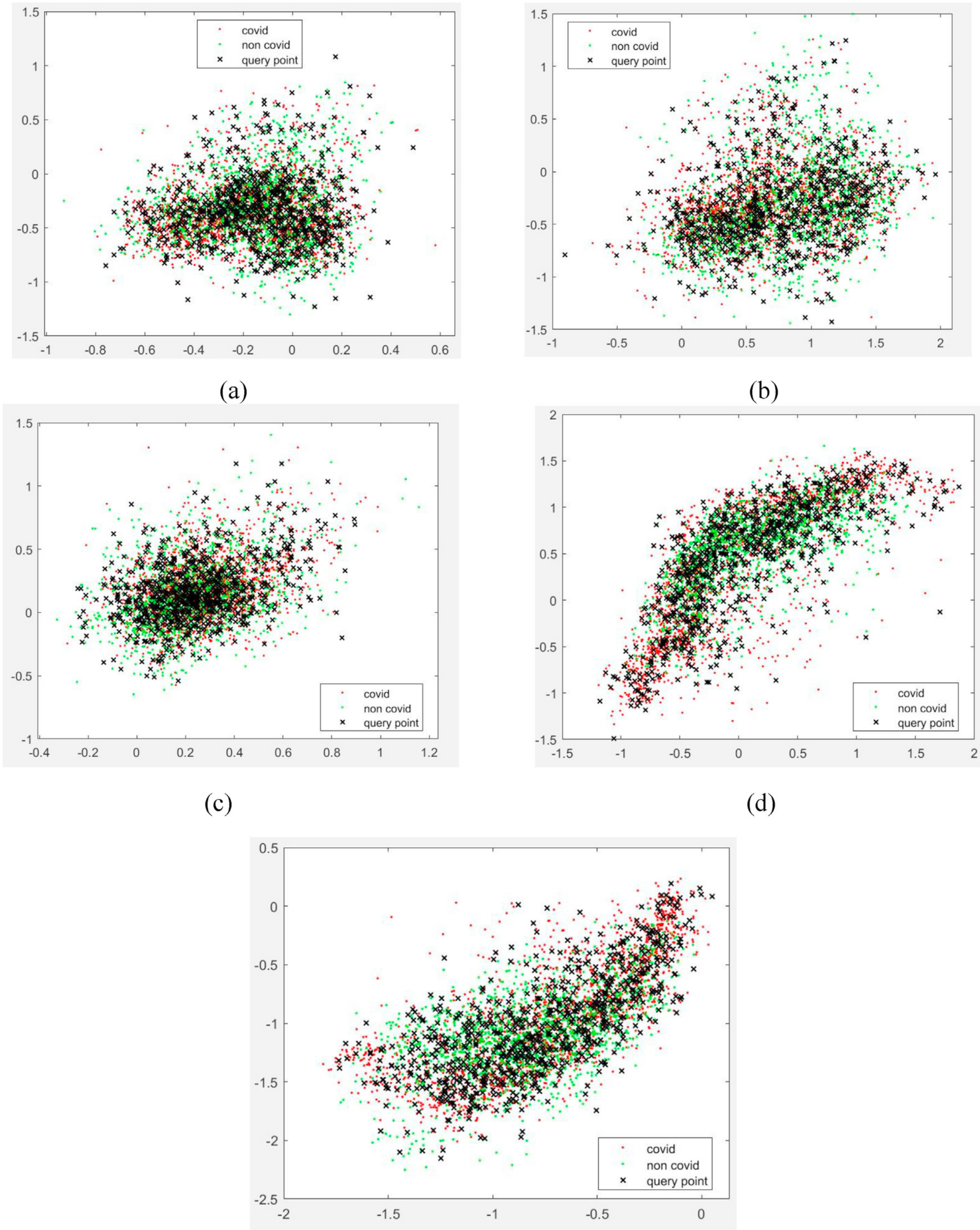

Fig. 8. Scattering plots of KNN for (a) 1st fold (b) 2nd fold (c) 3rd fold (d) 4th fold (e) 5th fold.

Here, R refers to the Euclidian distance between two points, $(x_i - y_i)$ represents the two points in the xy plane where i = 1,2,3, ….., N number of data points. For applying KNN, it is important to select a suitable value of K and a precise classification depends on this value [36]. In proposed work, the value of K or the number of nearest neighbors is taken 3. Distance between the features specified for training and testing samples is calculated in the KNN [37]. The majority voting class of training features used in the KNN algorithm is centered on Euclidian distance measurement. The equation of the majority rule algorithm is given below:

$$M.R = \sum_{L(a_i,b_i)\varepsilon D_r}^{argmax} I(L = b_i) \tag{8}$$

Here, M.R represents the majority voting rule, L refers to the label of the classes. B_i refers to the ith nearest neighbor of class labels. I represents the indication function uses binary values for representing true or false. The advantages of using the KNN classifier are that this is simple and effective compared to CNN and requires no training time.

The high-level features are taken out from the 4th convolutional layer those are used as input in KNN (K Nearest Neighbor) classifier. This

Table 5
Training hyper parameters.

Hyper Parameters	Specifications
Optimizer	ADAM
Validation Frequency	10
Initial Learning Rate	0.001
Batch size	163
Epochs	10
Learn rate drop factor	0.2
Iteration per epoch	25

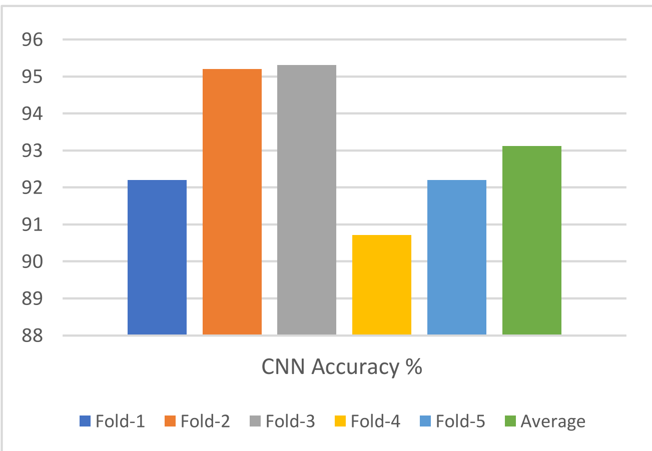

Fig. 9. Training and validation accuracy of CNN model for five folds F-validation.

classifier algorithm stores only the valuable features for classifying CT scans images of COVID-19 and non-COVID-19 patients based on the features closer to or known as neighboring features. The KNN classifier algorithm then takes features from testing images for prediction or classification. Here the total training and testing CT scans are 3268 and 817, respectively. The scattering plot of KNN for testing and training features for samples are given in Fig. 8.

Here we obtain 5 scattering plots as the augmented dataset is split into 5- folds. In each fold, the training images and testing images are dissimilar. So, due to different training and testing samples, we obtain 5 sets of training and testing features. A scattering plot is used for visualizing the relationship between the training and testing features. In Fig. 8, the training features for covid and non-covid are marked as red dots and green dots, respectively. The testing features or point is represented by query point (see Table 4).

Table 6
Accuracy for both CNN and CNN–KNN.

Fold Number	CNN Accuracy %	CNN–KNN Accuracy %
Fold-1	92.2	97.9
Fold-2	95.2	98.3
Fold-3	95.3	99.0
Fold-4	90.7	98.2
Fold-5	92.2	97.9
Average	**93.12**	**98.26**

5. Result analysis

5.1. Training hyperparameters

To train the CNN model, 'adam' optimizer is used where the learning rate is 0.001. Adam optimizer is selected over 'sgdm' optimizer and this optimizer is performing better on the augmented dataset. As in 'adam', it merges two different optimizers (i.e rmsprop and adagrad) [38]. This optimizer is performing better on the augmented dataset. There is a list of hyperparameters in Table 5.

For fitting the training images(data) with the CNN model, 163 batch size is taken. The validation frequency for training the CNN model is 10. The proposed model is run with 10 epochs where iteration per epoch is 25. After every 5 epochs the learning rate is decreased by using a learning rate drop factor of 0.2. Fig. 9 Shows the training progress for 5-fold cross-validation (see Fig. 10).

The epoch for training the CNN model is taken 10 because the error rate did not change after 10 epochs and training graph has got saturated. In Fig. 9, after 10 epochs, the CNN model has acquired the highest accuracy for five folds and validation accuracy acquired from each 5-fold cross-validation are 92.2%, 95.2%, 95.3%, 90.7%, 92.2%. The average validation accuracy is 93.12% which is shown in Table 6 (see Fig 11).

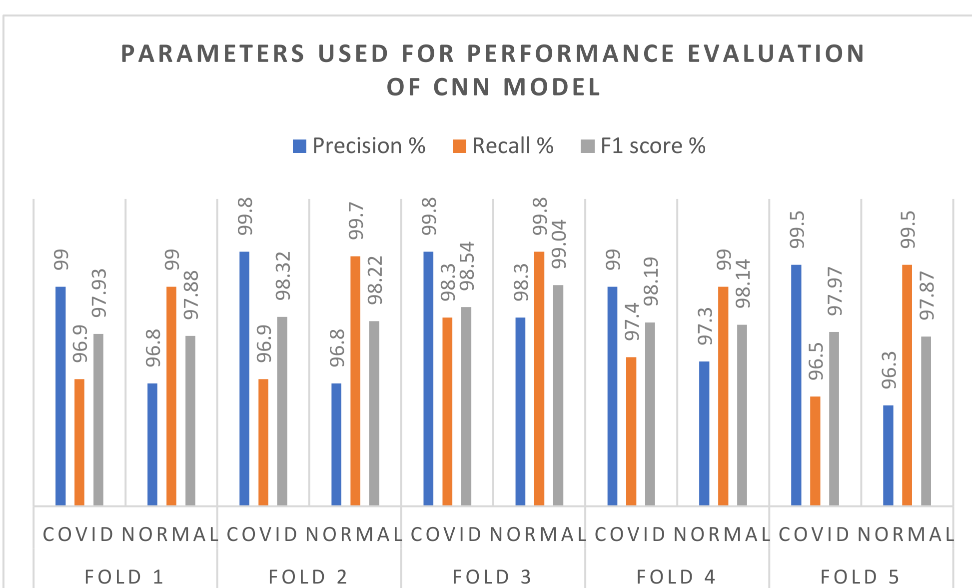

Fig. 10. Parameters used for Performance Evaluation of CNN Model.

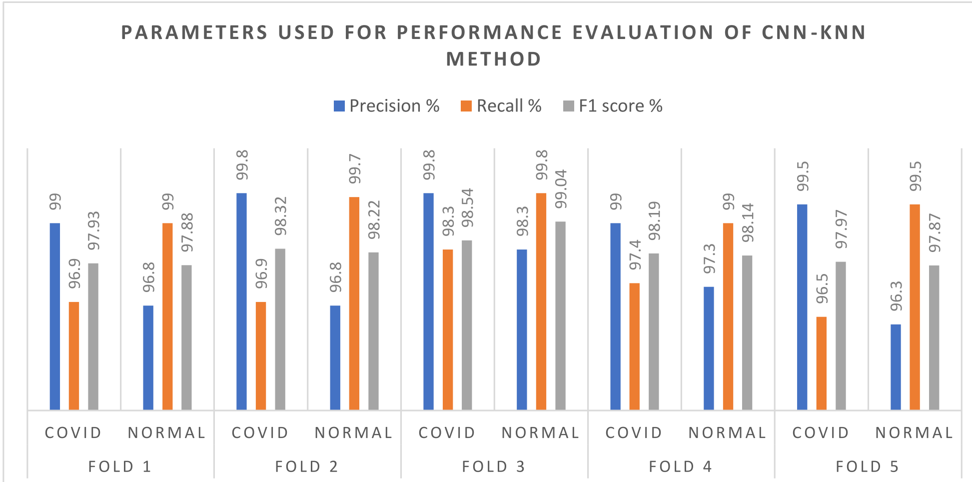

Fig. 11. Parameters used for Performance Evaluation of CNN Model.

Table 7
Confusion matrix of CNN–KNN for fold-1.

CONFUSION MATRIX		PREDICTED	
		COVID	NON-COVID
ACTUAL	COVID	408	13
	NON-COVID	4	392

Table 8
Confusion matrix of CNN–KNN for fold-2.

CONFUSION MATRIX		PREDICTED	
		COVID	NON-COVID
ACTUAL	COVID	410	13
	NON-COVID	1	392

Table 9
Confusion matrix of CNN–KNN for fold-3.

CONFUSION MATRIX		PREDICTED	
		COVID	NON-COVID
ACTUAL	COVID	410	7
	NON-COVID	1	399

Table 10
Confusion matrix of CNN–KNN for fold-4.

CONFUSION MATRIX		PREDICTED	
		COVID	NON-COVID
ACTUAL	COVID	407	11
	NON-COVID	4	395

5.2. Improved performance with KNN

The CNN uses the softmax activation function for the classification and this only works with training data, so the result got biased towards training so using KNN after CNN can lessen biasing that means KNN regularizes CNN result using extracted features.

6. Performance evaluation

After distinguishing the actual and predicted classes from confusion matrices following equations are used to mathematically estimate the performance of the proposed CNN and CNN–KNN hybrid model in Table .12 and Table .13. These confusion matrices are obtained from the KNN classifier shown in Table 7–Table 11.

The true positive rate of Covid-19 images for all the 5-folds is 408, 410, 410,407 and 409, respectively, where the actual number of testing Covid-19 CT scans was 411. Similarly, the true positive rate of normal CT scans for all folds is 392, 393, 395,399 and 391, respectively, where the actual number of testing normal CT scans was 406. This shows that the

Table 11
Confusion matrix of CNN–KNN for fold-5.

CONFUSION MATRIX		PREDICTED	
		COVID	NON-COVID
ACTUAL	COVID	409	15
	NON-COVID	2	391

Table 12
Comparison of the proposed hybrid CNN–KNN with existing methods with same dataset.

Study	Method	Accuracy%
Cai [13]	ResNet-34	94.3
Soares [14]	XDNN	88.6
Panwar [16]	VGG19	95
Wang [39]	Redesigned COVID-NET	90.83 ± 0.93
Jaiswal [40]	Transfer Learning + CNN	97
Chaudhary and Pachori [41]	FBSED + CNN	97.6
Konar [42]	Semi Supervised SL Network	89–94.4
Proposed	**CNN–KNN**	**98.26%**

Table 13
Comparison of the proposed hybrid CNN–KNN with existing methods with different dataset.

Author	Chest Data Type	Method	2 Class Accuracy
Ying [20]	CT	DRE-Net	86.0%
Zheng [18]	CT	UNet+3D CNN	90.8%
Wang [43]	CT	M-Inception	82.9%
Sen [44]	CT	Bi-stage feature + CNN	90.0%
Zhu [45]	CT	Transfer Learning	95.8%
Proposed Method	**CT**	**CNN + KNN**	**98.26%**

true positive rate is higher and thus, the performance evaluation parameters precision and recall will be higher and the accuracy of the proposed model.

Here, 'true positive' defines the state when a COVID-19 patient is correctly detected as a COVID-19 patient. The term 'false positive' denotes the wrong identification of a COVID-19 patient, which means when a non-COVID-19 person is recognized as a patient of COVID-19. When a covid negative person is correctly identified, it is said to be true negative. The phrase 'false negative' defines the case when a COVID-19 patient is analyzed as a negative patient.

The average precision, recall and F1 score for covid positive patients are 92.04%, 94.2% and 93.07%, respectively. For the covid negative patient, the average precision, recall and F1 score are 94.24%, 92.18% and 92.96%, respectively.

The average precision, recall and F1 score for covid positive patients are 99.42%,97.2% and 98.19%, respectively.

For the covid negative patient, the average precision, recall and F1 score are 97.1%,99.4% and 98.23%, respectively.

7. Comparison

Several papers [13,14,16,39–42] experimented on the same dataset to detect COVID-19 patients. To compare the result obtained from the proposed hybrid method with previous studies, those who applied the deep learning method on CT scan images are listed in Table .12.

Different deep learning techniques are used in Refs. [13,14,16,39,40] for COVID-19 classifications. Transfer learning is applied on [13,14,16,38] and feature extraction is manipulated by pre-trained GoogleNet in Ref. [14]. Transfer learning means taking a deep learning model which was trained on an enormous dataset with higher accuracy and an approach of reusing model weights of that benchmark dataset mainly, ImageNet. The architectures of pre-trained models for transfer learning are complex and have a higher number of parameters. The proposed method is simple in contrast with a pre-trained network. Also, the algorithm can implement over conventional PC. The benefit of designing a smaller network is related to the potentiality of implementing an algorithm on mobile devices, which is critical in developing countries for diagnostics. Comparisons with existing methods that used deep learning with CT scan images are listed in Table 13.

From the above comparison, it is seen that the proposed CNN–KNN-based approach shows better accuracy. The significance of the above comparison is that, without using the same dataset, the hybrid models have less accuracy than the proposed one on a large scale. In Ref. [43], the proposed model is a hybrid with a pretrained model. In Ref. [18], the CNN model used, was a three-dimensional model and [44] used transfer learning. In this proposed work, a conventional CNN model is combined with K-Nearest Neighbor classifier skipping the fully connected layers of the CNN model.

This proposed method is unique because the feature extraction is done automatically from the 4th convolutional layer of the proposed CNN architecture and directly input to the KNN classifier, which is faster and simple compared to using the direct classifier. The hybrid architecture of CNN and KNN classifier makes the proposed method works better because by avoiding the softmax classification of CNN, features go to the KNN classifier. Compared to the softmax classifier, the KNN classifier gets stronger gradually because of the backpropagation of the cross-entropy loss of the classification of training images. Also, the KNN classifier reduces intra-class distance and pulls the training and validation data closer and bounded the classification error.

8. Conclusion

The proposed hybrid model is designed to classify whether a patient is COVID positive or COVID negative. In this case, instead of using a pre-trained CNN architecture, a self-designed CNN architecture combined with KNN is implemented to accurately classify COVID positive and negative patients. K-fold is applied to generalize the CT scan dataset. The application of the two different algorithms makes this method robust. Here, high-level features of CNN are classified through the KNN algorithm. Instead of using a fully connected layer for classification KNN is preferred to classify the 4th convolutional layer's 10,752 high level features of each image. There are some limitations of the proposed work like, the average accuracy of the CNN model is 93.12% which can be improved in future by building more complex architecture. If the CNN model can give better performance than this proposed one then the extracted features will be much more accurate and classifiers will also achieve higher evaluation matrices. However, the average accuracy gained from the KNN classifier is 98.26%. As a result, the proposed method may be regarded an efficient method for detecting COVID-19 patients using a CT scan.

Declaration of competing interest

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

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