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Research Article

A CNN-based hybrid model to detect Coronavirus disease

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Abstract

In this paper, a hybrid classification technique for COVID-19 disease is proposed. The proposed model solves the two-class classification problem (covid, normal). In this study, we have presented hybrid models integrating superior deep learning and machine learning classifiers: Convolutional Neural Network (CNN) and Support Vector Machine (SVM), CNN and AdaBoost, CNN and K Nearest Neighbour (kNN), CNN and Multilayer Perceptron (MLP), CNN and Naive Bayes (NB). In these models, CNN performs as a trainable deep feature extractor, and SVM, AdaBoost, kNN, MLP, NB behave as recognizers. All experiments have been performed on COVID-CT and SARS-CoV-2 CT combined image datasets. As a result, proposed hybrid methods have been compared in terms of sensitivity, accuracy, precision, F1-score, AUC-score, specificity, FPR, FDR, and FNR. CNN+SVM, CNN+MLP, and CNN+kNN have achieved outperforming results according to the other models. Also, CNN+SVM performed the best. When the results are examined, the proposed hybrid system is seen to be efficient to detect COVID-19. Also, the performance of the proposed hybrid system is better than the successful studies found on COVID-CT and SARS-CoV-2 CT combined image datasets in the literature.

Keywords: Covid-19, hybrid models, deep learning, CNN.

Koronavirüs hastalığını tespit etmek için CNN tabanlı bir hibrit model

Öz

Bu yazıda, COVID-19 hastalığı için hibrit bir sınıflandırma tekniği önerilmektedir. Önerilen model, iki sınıflı sınıflandırma problemini çözmektedir (covid, normal). Bu çalışmada, üstün derin öğrenme ve makine öğrenimi sınıflandırıcılarını entegre eden hibrit modeller sunduk: Evrişimsel Sinir Ağ (CNN) ve Karar Destek Makinesi (SVM), CNN ve AdaBoost, CNN ve K En Yakın Komşu (kNN), CNN ve Çok Katmanlı Algılayıcı (MLP), CNN ve Naive Bayes (NB). Bu modellerde CNN, eğitilebilir bir derin özellik çıkarıcı olarak çalışır ve SVM, AdaBoost, kNN, MLP, NB bir tanıyıcı olarak davranır. Tüm deneyler, COVID-CT ve SARS-CoV-2 CT birleşik görüntü veri kümeleri üzerinde gerçekleştirilmiştir. Sonuç olarak, önerilen hibrit yöntemler duyarlılık, doğruluk, kesinlik, F1 puanı, AUC puanı, özgüllük, FPR, FDR ve FNR açısından karşılaştırılmıştır. CNN + SVM, CNN + MLP ve CNN + kNN, diğer modellere göre sırasıyla daha iyi performans gösteren sonuçlar elde etmiştir. Ayrıca, CNN + SVM en iyi performansı göstermiştir. Sonuçlar incelendiğinde, önerilen hibrit sistemin COVID-19'u tespit etmede etkili olduğu görülmektedir. Ayrıca, önerilen hibrit sistemin performansı, literatürdeki COVID-CT ve SARS-CoV-2 CT birleşik görüntü veri kümelerinde bulunan başarılı çalışmalardan daha iyidir.

Anahtar Kelimeler: Covid-19, hibrit modeller, derin öğrenme, CNN.

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1. Introduction

At the last days of 2019, Coronavirus disease of 2019 (COVID-19) has emerged in China and quickly disseminated to the globe. The number of infected cases is increasing rapidly in many countries. Early diagnosis of disease is very important in terms of quarantine of infected cases (KARAKUŞ, 2020).

The clinical symptoms (cough, shortness of breath, etc.) of the disease are not specific, so the detection progress is challenging. The reverse-transcription polymerase chain reaction (RT-PCR) test is a generally employed standard technique to detect the disease. However, it has many shortcomings including resulting in false-negatives and being time-consuming.

Computed tomography (CT) is a well-known imaging technique for a successful and early recognition of the disease. Thus, radiological imaging is important as a diagnostic tool. The computer-aided design (CAD) systems that use CT images are recommended for the control and the interpretation of the disease case. These systems are critical for helping radiologists in accurately diagnosing the disease based on medical image data.

Numerous articles have been published in the literature recently. Especially, the classification of the CT images was conducted via artificial intelligence techniques and successful results have been obtained, as the following paragraph discusses.

In their study, Wu et al. applied ResNet50 on 368 COVID-19 CT images from Beijing Youan Hospital and China Medical University. They achieved accuracy, sensitivity, specificity, and AUC rates of 76%, 81.1%, 61.5%, and 81.9%, respectively (Wu et al., 2019). Jin et al. applied ResNet152 on 1881 COVID-19 CT images from Wuhan Union Hospital, Jianghan Mobile Cabin Hospital, and Western Campus of Wuhan Union Hospital. They achieved accuracy, sensitivity, specificity, precision, F1-score, and AUC rates of 94.98%, 94.06%, 95.47%, 91.53%, 92.78%, and 97.91%, respectively (Jin et al., 2020). Javaheri et al. applied BCDU-Net on 32230 covid data from five medical centers. They achieved accuracy, sensitivity, specificity, and AUC rates of 91.66%, 87.5%, 94%, and 95%, respectively (Javaheri et al., 2020). Jin et al. applied different DL based algorithms (DPN-92, Inception-v3, ResNet-50, Attention ResNet50 with 3D U-Net++) on 1391 COVID-19 CT images from five different hospitals of China. They achieved AUC, sensitivity, and specificity rates of 99.1%, 97.04%, and 92.2%, respectively (Jin et al., 2020). Chen et al. applied Unet++ on 35355 CT images from the Renmin Hospital of Wuhan University. They achieved accuracy, sensitivity, specificity, precision, and AUC rates of 98.85%, 94.34%, 99.16%, 88.37%, and 99.4%, respectively (Chen et al., 2020). Ardakani et al. applied DL based algorithms (AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101, Xception) on 510 CT images from real-time data. They achieved accuracy, sensitivity, specificity, precision, and AUC rates of 99.51%, 100%, 99.02%, 99.27%, and 99.4%, respectively (Ardakani et al., 2020). He and his colleagues proposed CRNet in their work. With this model, they have reached an 86% accuracy rate, 85% F1-score, and 94% AUC (He et al., 2020). Wang et al. proposed the Modified-Inception model for classification. They have reached 79.3% accuracy rate, 83% sensitivity, 67% specificity, 55% precision, 63% F1-score, and 81% AUC (Wang et al., 2020). Ying et al. suggested DRE-Net on 777 COVID positive CT data from the Third Affiliated Hospital and Hospital of Wuhan University. With this model, they have reached 94.3% accuracy rate, 93% sensitivity rate, 96% precision rate, 94% F1-score, and 99% AUC (Song et al., 2020). Zheng et al. applied DeCoVNet on 630 CT images from three different hospitals (Huazhong University of Science and Technology, Union Hospital, and Tongji Medical College). They achieved accuracy, sensitivity, specificity, precision, and AUC rates of 90.1%, 90.7%, 91.1%, 84%, and 95.9%, respectively (Zheng et al., 2020). Singh et al. proposed MODE-CNN in their work. With this model, they have reached a 93.25% accuracy rate, 90.70% sensitivity rate, 90.72% specificity rate, and 89.96% F1-score (Singh et al., 2020). Farid et al. applied a CNN model on 51 COVID-19 CT images from the Kaggle benchmark dataset. They achieved accuracy, precision, F1-score and AUC rates of 94.11%, 99.4%, 94%, and 99.4%, respectively (Farid et al., 2020). The writers in Wang et al. suggested employing the Inception and Adaboosted decision tree framework. They recognized COVID-19 cases achieving an accuracy of 82.9%, an AUC of 90%, a sensitivity of 81%, and a specificity of 84% (Wang et al., 2020). The writers in Song et al. presented a ResNet-50 architecture. The accuracy, AUC, sensitivity, and precision values proved to be 86%, 95%, 96%, and 79%, respectively (Song et al., 2020). The researchers in Jin et al. used the Deeplab-v1 and ResNet-152 deep learning framework to make a distinction between COVID-19 and non-COVID-19 cases. An accuracy of 94.8%, an AUC of 97.9%, a sensitivity of 94.1%, and a specificity of 95.5% were obtained (Jin et al., 2020).

Other studies proposed DL-based architectures for novel coronavirus pneumonia (NCP) diagnosis. However, as it is observed, the effectiveness of CNN-based deep hybrid approaches can more be required in the literature. Therefore, in this paper, CNN architecture was used as a basic network for a hybrid model approach.

2. Material and Method

2.1. Material

Two public datasets are used to predict and evaluate our framework, including COVID-CT (Yang et al., 2020; 2020) and SARS-CoV-2 CT-scan image datasets (Soares et al., 2020; 2020) (Fig. 1).

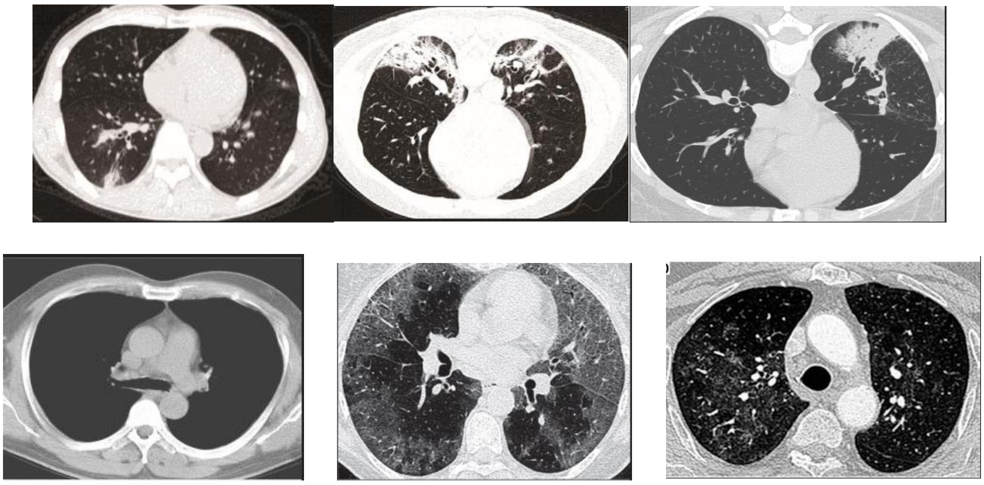

Figure 1 Examples of CT Images (COVID-19 (Top) and Non-COVID-19 (Bottom))

SARS-CoV-2 CT-scan dataset is composed of CT scan images that were collected from hospitals in Brazil. This dataset consists of 2482 CT scans from 120 cases, with 1252 CT scans of 60 cases infected and 1230 CT scans of 60 cases non-infected by SARS-CoV-2. COVID-CT dataset is composed of CT images of patients infected with SARS-CoV-2, These were obtained from the research articles. This dataset consists of 349 CT scans from 216 patients. Metadata is associated with properties like patient gender, age, scan time, the severity of the disease, etc. Regarding to non-covid patients, this dataset consists of 463 CT scans from 55 patients. These images were collected from websites, articles, and other resources.

In this paper, SARS-CoV-2 CT-scan and COVID-CT images are combined. The combined dataset consists of 3227 CT images, with 1601 covid and 1626 non-covid cases.

2.2. The proposed framework

In this study, five different DL-based hybrid models are applied to predict and evaluate the classification results. These models are used on the combined image dataset.

The proposed hybrid system uses the deep features derived from CNN separately and utilizes these features to train SVM, AdaBoost, kNN, MLP, and NB classifiers. Then, the classification performance of the classifiers is evaluated (Fig. 2).

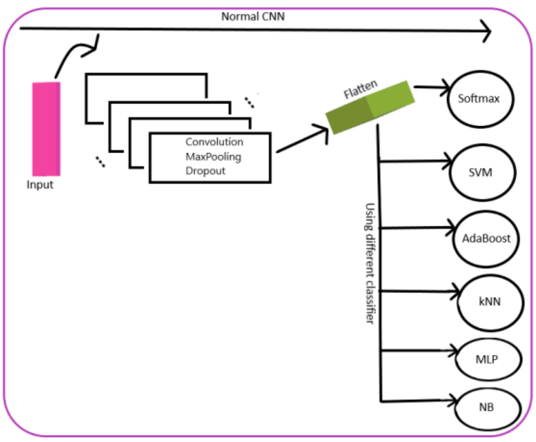

Figure 2 The Architecture of The DL Based-CAD System

A convolutional neural network is one of the deep learning architectures. This architecture is usually composed of the following types of layers: convolutional, activation, dropout, pooling, and softmax (Fig. 3). Convolutional neural networks vary in how convolutional and other sublayers are trained and implemented.

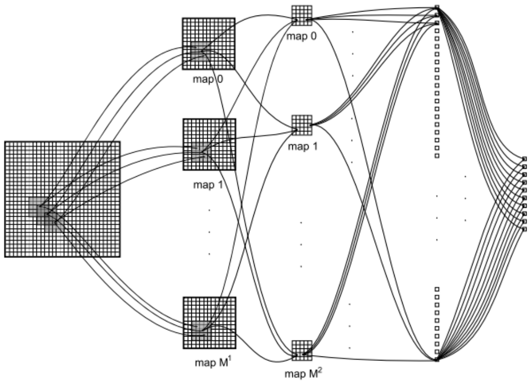

Figure 3 General Architecture of A CNN [Ciresan et al., 2011]

The convolutional layer provides producing feature maps. This layer has trainable bias and trainable filters per feature map. Each output map is connected to all of its preceding feature maps. The convolution process is presented in Eq. (1) (Yildirim & Cinar, 2020). In Eq. (1); x, w, t, and s represents the input, filter, times, and result, respectively.

$$s(t) = (x * w)(t) = \sum_{n=-\infty}^{\infty} (x(n) + w(t-n)) \quad (1)$$

Activation functions are important to help the model to learn better. The activation function is usually used for nonlinear transformation. Relu was preferred for this study (Eq. (2)) (Yildirim & Cinar, 2020). The obtained output feature maps with the convolutional layer are passed to this layer.

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}, \quad f(x)' = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \quad (2)$$

Then, while moving to the next layer, a maximum pooling process is applied to reduce the spatial size of the input (Eq. (3) (Yildirim & Cinar, 2020)). In Eq. (3); w, h, and d represents width, height, and depth of input image size, respectively. Also, the dropout method was used to improve the performance of the model. This technique prevents overfitting. The softmax layer is used to predict the classification label for the final result.

$$S = w * h * d \quad (3)$$

CNN architecture has been used as the basic structure in the hybrid models. The improved hybrid model structure was presented in Fig. 2. At the last layer of the CNN, instead of the softmax function, SVM, AdaBoost, kNN, MLP, and NB were implemented, respectively.

For consistency, all the images are resized to 256 x 256 x 3. That is, the image input sizes are updated as 256*256 with three channels. CNN model was used for the feature extraction. Details of CNN architecture are presented in Table 1.

Features were obtained from the Flatten layer of the CNN architecture. The box plot illustration of the features obtained from the CNN model is given in Fig. 4. The feature values from the CNN model were in a wide range. Also, the box plot illustration of the value of each feature is given in Fig. 5.

Table 1 Details of Layers Used in CNN

Layer	**Stride**	**Filter size**	**Pool size**	**Padding**	**Activation**	**Data depth**	**No. of parameters**
Input Layer	-	-	-	-	-	3	0
Conv1	1	5x5	-	Same	Relu	16	1216
MaxPooling	2	-	2x2	-	-	16	0
Dropout	-	-	-	-	-	16	0
Conv1	1	5x5	-	Same	Relu	32	12832
MaxPooling	2	-	2x2	-	-	32	0
Dropout	-	-	-	-	-	32	0
Conv1	1	5x5	-	Same	Relu	64	51264
MaxPooling	2	-	2x2	-	-	64	0
Dropout	-	-	-	-	-	64	0
Conv1	1	5x5	-	Same	Relu	64	102464
MaxPooling	2	-	2x2	-	-	64	0
Dropout	-	-	-	-	-	64	0
Flatten	-	-	-	-	-	64	0

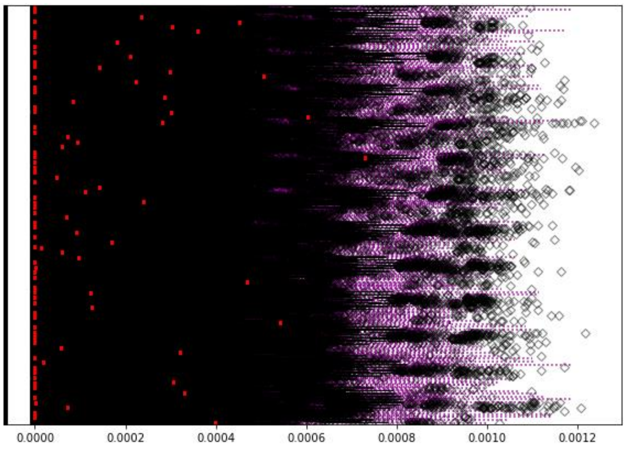

Figure 4 The Illustration of the Feature Values from CNN Model

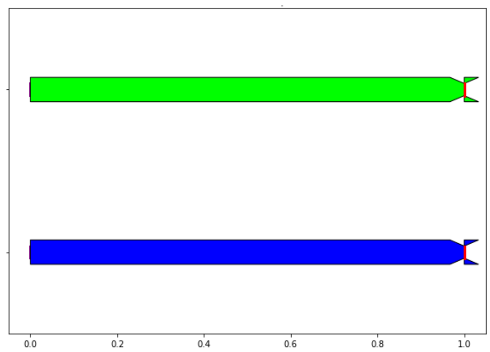

Figure 5 The Illustration of the Target Feature from CNN Model

Later, these features are used in the classification stage of the proposed framework. The classification stage uses 5 different machine learning classifiers. These are SVM, AdaBoost, kNN, MLP, and NB algorithms (Fig. 2).

2.3. Support vector machine, Adaptative boosting, K nearest neighbor, Multilayer perceptron, Naive bayes

The support vector machine (SVM) was first introduced by Vapnik (Cortes, 1995) for classification and regression. The basic idea of the algorithm is to find the best hyperplane (Eq. (4)). In Eq. (4); w, x, b, and f(x) represents a vector to the hyperplane, training data, bias, and class, respectively for a two-class problem.

$$f(x) = (w * x) + b(x \in \mathrm{R}^m) \quad (4)$$

Also, this method is proposed to solve multi-class problems. If the data cannot be separated linearly, a mapping function, called as kernel, is used to determine the hyperplane. So, the hyperplane can be formulated as in Eq. (5). In Eq. (6); $f(x_d)$, x_j, and x_d represents the class of new input data, a support vector, and input data, respectively.

$$min\frac{1}{2}||w||^2 = \min\frac{1}{2}w^T w \quad (5)$$

$$f(x_d) = \sum_{j=1}^{Ns} a_j y_j x_j x_d + b \quad (6)$$

Adaptative boosting (AdaBoost) was proposed by Freund and Schapire in 1996 (Freund & Schapire, 1997). It was developed for binary classification. This algorithm is an ensemble method and aims to convert a number of weak classifiers into a strong classifier. The final classifier is given in Eq. (7). In Eq. (7); $f_i(x)$, w_i, and t represents the i^{th} weak classifier, the weight, and the number of the weak classifiers, respectively.

$$f(x) = \begin{cases} 1, & if \sum_{i=1}^{t} w_i f_i(x) \geq threshold \\ 0, & otherwise \end{cases} \quad (7)$$

In the pattern recognition field, K Nearest Neighbor (kNN) is one of the non-parametric classifiers (Cover & Hart, 1967). The kNN classifier often uses the Euclidean distance metric for measuring the distances between the data points (Eq. (8)) (Witten & Frank, 2002).

$$D(i,j) = \sqrt{\sum_{t=1}^{m}(x_{it} - x_{jt})^2} \quad (8)$$

The multilayer perceptron (MLP) (Witten & Frank, 2002) has three layers: input, hidden, and output. It has neurons that map the input to the output class. The output y_t of a neuron t is given in Eq. (9). In Eq. (9); x_i, w_{ti}, and $\varphi(.)$ represents the input, the connection weight, and the activation function, respectively. In the input layer, the number of neurons is determined by the dimension of the input. In the output layer, the number of neurons is determined by the number of output classes. In the hidden layer, the number of the neurons is determined according to the best performance.

$$y_t = \varphi(\textstyle\sum_{i=0}^{m} x_i w_{ti}) \quad (9)$$

The Naive Bayes (NB) algorithm is based on Bayes Theorem (Russell & Norvig, 2002). Bayes Theorem is given in Eq. (10). In Eq. (10); $P(Y)$, $P(X|Y), P(X)$, and $P(Y|X)$ represents the probability of the class, conditional probability of the class for the given attribute, probability of the attribute, and the conditional probability that attribute belongs to the class, respectively.

$$P(Y|X) = \frac{P(Y)P(X|Y)}{P(X)} \quad (10)$$

3. Results

In this study, all the research is conducted by using Python language using a computer having an Intel(R) Core(TM) i7-7700 CPU, 24 GB memory, and GeForce GT 730 GPU (NVIDIA).

CT images were obtained for the disease detection. The training and test sets were randomly selected as 70% training and 30% test data based on the CT image data to analyze the classifier’s accuracy and performance.

3.1. Evaluation metrics

The performance of the proposed hybrid frameworks was measured with different metrics such as sensitivity, precision, accuracy, F1-score, AUC-score, specificity, FPR, FDR, and FNR. The formulations are shown below: (Eqs. (11) - (18)).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (12)$$

$$Specificity = \frac{TN}{TN + FP} \quad (13)$$

$$Precision = \frac{TP}{TP + FP} \quad (14)$$

$$F1 - score = \frac{2 \text{ x precision x sensitivity}}{TP + TN + FP + FN} \quad (15)$$

$$FPR = \frac{FP}{FP + TN} \quad (16)$$

$$FDR = \frac{FP}{FP + TP} \quad (17)$$

$$FNR = \frac{FN}{FN + TP} \quad (18)$$

In these equations, four statistical indices are calculated; namely, false negative (FN), true negative (TN), false positive (FP), and true positive (TP). FN is the number of covid images that are mistakenly classified as non-covid. TN is the number of non-covid images that are correctly classified. FP is the number of non-covid images mistakenly classified as Covid-19. TP is the number of covid images that are correctly classified.

Table 2 Performance of DL-based Hybrid Models

Method	Class	Sensitivity (%)	Precision (%)	Accuracy (%)	F1-score (%)	AUC-score (%)	Specificity (%)	FPR (%)	FDR (%)	FNR (%)
CNN+SVM	covid	**85.85**	**85.86**	**85.86**	**85.85**	**85.85**	**86.47**	**13.52**	**13.86**	**14.76**
CNN+AdaBoost	covid	73.68	73.68	73.68	73.68	73.68	73.77	26.22	26.55	26.40
CNN+kNN	covid	82.25	82.26	82.24	82.24	82.25	81.14	18.85	18.66	16.63
CNN+MLP	covid	82.35	82.35	82.35	82.35	82.35	81.96	18.03	18.10	17.25
CNN+NB	covid	53.29	56.47	53.04	46.62	53.29	18.23	81.76	48.42	11.64

The performance results of the proposed framework are shown in Table 2.

CNN+SVM performed the highest with a sensitivity of 85.85%, a precision of 85.86%, an accuracy of 85.86%, an F1-score of 85.85%, an AUC score of 85.85%, a specificity of 86.47%, an FPR of 13.52%, an FDR of 13.86%, and an FNR of 14.76%.

CNN+NB achieved the poorest performance with a sensitivity of 53.29%, a precision of 56.47%, an accuracy of 53.04%, an F1-score of 46.62%, an AUC score of 53.29%, a specificity of 18.23%, an FPR of 81.76%, an FDR of 48.42%, and an FNR of 11.64%.

CNN+MLP model demonstrated higher accuracy (82.35%) than CNN+kNN (82.26%) and CNN+AdaBoost (73.68%). Also, with respect to sensitivity, precision, F1-score, AUC score, and specificity, the results show that the CNN+MLP model achieved higher performance than CNN+kNN and CNN+AdaBoost (Fig. 6).

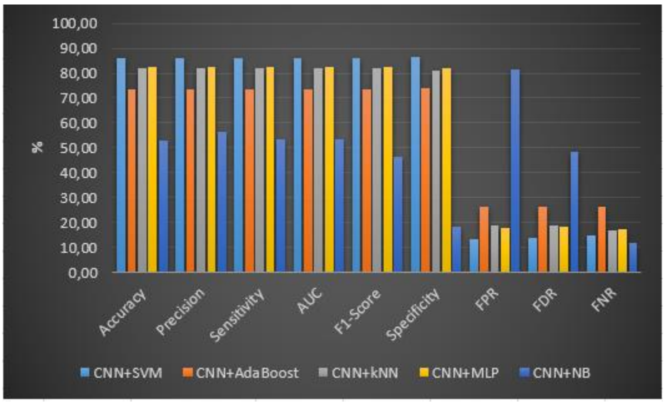

Figure 6 The Comparison of Accuracy, Precision, Sensitivity, AUC, F1-score, Specificity, FPR, FDR, and FNR for Each Model

A Confusion matrix is a metrics used to obtain the accuracy, precision, sensitivity, specificity, F1-score, FPR, FDR, and FNR of the model described in Equations (11-18). Table 3 shows true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) based on two classes (covid, normal).

Table 3 Confusion Matrix of the Observed Deep Learning Algorithms on Dataset

Method	Actual Classes	Predicted	
		Covid	normal
CNN+SVM	Covid	410 (TP)	71 (FN)
	Normal	66 (FP)	422 (TN)
CNN+AdaBoost	Covid	354 (TP)	127 (FN)
	Normal	128 (FP)	360 (TN)
CNN+kNN	Covid	401 (TP)	80 (FN)
	Normal	92 (FP)	396 (TN)
CNN+MLP	Covid	398 (TP)	83 (FN)
	Normal	88 (FP)	400 (TN)
CNN+NB	Covid	425 (TP)	56 (FN)
	Normal	399 (FP)	89 (TN)

To the best of our knowledge, the performance comparison of hybrid models (deep learning + machine learning) is limited on the combined image datasets. Table 4 shows the related studies which are using the same datasets. Wang et al. (2020) studied the Parallel Adapter algorithm to predict disease on the SARS-CoV-2 CT-scan dataset and obtained an accuracy of 82.13%. Wang et al. (2020) also studied with SepNorm+Contrastive to predict disease on the COVID-CT dataset and obtained an accuracy of 78.69%. Polsinelli et al. (2020) studied with CNN to predict disease on the COVID-CT dataset and obtained an accuracy of 83%. Saeedi et al. (2020) studied with ResNet50V2 to predict disease on the COVID-CT dataset and obtained an accuracy of 84.03%. Silva et al. (2020) studied EfficientNet Based Model to predict disease on combined image dataset and obtained an accuracy of 59.12%. In this context, the CNN+SVM hybrid model outperformed the best study ever reported in the literature in terms of performance metrics on the combined dataset.

Our proposed CNN method has fewer hidden layers in the proposed DL-based hybrid approach. We think that if CNN is trained with more neurons or more hidden layers or on a large amount of data, it can achieve higher accuracy results than 85.86%.

Table 4 Comparison with the Studies in the Literature

Approach	Dataset	Method	Accuracy(%)
Polsinelli et al. (2020)	COVID-CT	CNN	83
Silva et al. (2020)	SARS-CoV-2 CT-scan + COVID-CT	EfficientNet Based Model	59.12
Wang et al. (2020)	SARS-CoV-2 CT-scan	Parallel Adapter	~82.13
Wang et al. (2020)	SARS-CoV-2 CT-scan	Joint (Redesignt	~78.42
Wang et al. (2020)	SARS-CoV-2 CT-scan	Single (COVID-Net)	~77.12
Wang et al. (2020)	COVID-CT	Single (Redesign)	~77.07
Wang et al. (2020)	COVID-CT	Joint (Redesign)	~69.67
Wang et al. (2020)	COVID-CT	MS-Net	~76.23
Wang et al. (2020)	COVID-CT	SepNorm+Contrastive	~78.69
Saeedi et al. (2020)	COVID-CT	InceptionV3	~81.63
Saeedi et al. (2020)	COVID-CT	ResNet50V2	~84.03
Saeedi et al. (2020)	COVID-CT	ResNet50V1	~73.72
Proposed	SARS-CoV-2 CT-scan + COVID-CT	**CNN+SVM**	**85.86**

4. Conclusions

In this work, we proposed a framework for COVID-19 prediction. For the diagnosis, we applied DL-based hybrid architectures on CT combined datasets. CNN features were given to the machine learning classifiers (SVM, kNN, AdaBoost, MLP, NB) to measure the classification performance in a deep hybrid approach. CNN model consists of 4 convolutional layers, 4 max-pooling layers, and 4 dropout layers. These models automatically extract features from the input data and later generate COVID-19 predictions with machine learning techniques.

Model performance value is evaluated in terms of sensitivity, precision, accuracy, F1-score, AUC-score, specificity, FPR, FDR, and FNR. Experimental results are acquired with CNN+SVM, CNN+AdaBoost, CNN+kNN, CNN+MLP, and CNN+NB. With the developed CNN+SVM model, the highest accuracy rate of 85.86% is achieved.

The results can be improved by a larger CT dataset or by employing different CNN architectures. In the future, we will use different types of classifiers and different CNN architectures to improve the classification performance.

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