Diagnosis of COVID-19 in CT image using CNN and XGBoost

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***Abstract*—Coronavirus disease (COVID-19) has infected more than 3.6 million people worldwide and it is responsible for more than 250,000 deaths. A major problem faced in the diagnosis of COVID-19 is the inefficiency and scarcity of medical tests. The use of computed tomography (CT) has shown promise for the evaluation of patients with suspected COVID-19 infection. CT exam analysis is complex and requires specialist effort, which can lead to diagnostic errors. The use of CAD systems can minimize the problems generated by the analysis of CTs by specialists. This paper presents a methodology for diagnosing COVID-19 using convolutional neural network (CNN) for feature extraction in CT exams and its classification using XGBoost. The methodology consists of using a CNN to extract features from 708 CTs, 312 with COVID-19, and 396 Non-COVID-19. After the extracted data, we used XGBoost for classification. The results show an accuracy of 95.07, recall of 95.09, precision of 94.99, F-score of 95, AUC of 95, and a kappa index of 90. The results obtained show that the proposed methodology can be used as a diagnostic aid system by specialists.**

***Index Terms*—COVID-19, CT, diagnosis, classification, CNN, XGBoost, CAD**

I. Introduction

Coronavirus disease (COVID-19) is a respiratory disease caused by infection with the coronavirus of severe acute respiratory syndrome 2 (SARS-CoV-2) [1]. COVID-19 has infected more than 3.6 million people worldwide and it is responsible for more than 250,000 deaths [2]. A major problem faced in the diagnosis of COVID-19 is the inefficiency and scarcity of medical tests. In this regard, several efforts were devoted to searching alternative methods of diagnosing COVID-19.

Computed tomography (CT) is considered promising for the evaluation of patients with suspected COVID-19 infection [3]. CT manifests clear radiological findings from patients with COVID-19, serving as a more efficient and accessible test method [4]. The main problem with this method is that it depends on the specialist to analyze the CT images, as the process is repetitive, time-consuming and tiring for the specialist, due to numerous images to be analyzed, causing fatigue, which can lead to errors in diagnosis [5]–[7].

To minimize the problems generated by the analysis of images by specialists, computer-aided diagnosis (CAD) appears as an alternative aid to medical diagnosis. CAD systems use image processing and analysis techniques, and computational power to analyze images, being crucial for cases where a diagnosis is very difficult for the human eye [8], [9].

Recently, the use of deep learning methods has been implemented in the development of CAD systems. Convolutional neural networks (CNN), which are deep learning techniques, can automatically interpret CT images and predict whether they are positive for COVID-19 [10]. However, the complexity of the model, difficulty in training, high computational cost, and the need for a large data set, makes it difficult to develop a methodology with an effective application.

For the training and efficient classification of a CNN model, a large CT data set is required. As our data set has only 708 CT images, the training of a CNN model is complex. Thus, we used pre-trained CNNs to extract features and the eXtreme Gradient Boosting (XGBoost) to classify the CT images. XGBoost is a machine learning algorithm which is based on a decision tree and it uses a gradient boosting structure. XGBoost receives the set of features extracted by CNN and performs the prediction.

The proposed work aims to present the development of a method for classifying CT images in COVID-19 and Non-COVID-19 using pre-trained CNN for feature extraction and XGBoost for classification. The rest of this article is organized as follows. In Section II, we discuss related work. In Section III, we present the methodology used to extract features and classify the images. In Section IV, we present and discuss the results obtained. Finally, in Section V we present the conclusions and future work.

II. Related works

The development of CAD systems to aid in medical diagnosis using deep learning techniques has shown to be very promising. Deep learning techniques can be implemented in CAD systems for features extraction, classification or extraction and classification. The efficiency of a CAD system is related to the techniques that compose it. In this sense, the literature shows studies using deep learning techniques for diagnosing COVID-19.

Recently, several studies have been using CNN in the development of CAD systems for diagnosing COVID-19 [4],

[11]–[13]. This is because when using convolutional neural networks, there is no need for an explicit step of feature extraction and selection [14]. Abbas et al. [11] developed a methodology for the detection and diagnosis of COVID-19 using CNNs for classification and recognition. They used 80 Non-COVID-19 images and 126 images for positive COVID-19. The methodology consists of a CNN architecture called Decompose, Transfer, and Compose (DeTraC), for the classification of chest X-ray images with COVID-19. The use of DeTraC brought very effective and robust solutions for the classification of COVID-19 cases and the ability to deal with data irregularities. The results show an accuracy of 95.12%, sensitivity of 97.91%, specificity of 91.87%, and precision of 93.36%.

The work developed by Narin et al. [13] presents a methodology for automatic detection of COVID-19 in X-ray images using CNN. The methodology uses chest X-ray images from 50 patients with COVID-19 and 50 Non-COVID-19. The images were subjected to three different pre-trained CNN models, ResNet50, InceptionV3, and InceptionResNetV2. The methodology was validated using the ROC curve and metrics calculated from the confusion matrix in the three models, with cross-validation k-folds with k = 5. The results show an accuracy for the proposed models of 98% for ResNet50, 97% for InceptionV3 and 87% for Inception-ResNetV2.

Zhao et al. [12] presents a data set of scanning CT images of COVID-19. The methodology presents a COVID-CT data set with 275 CT exams for the development of research in COVID-19. They performed tests on the data set using a deep learning technique to predict whether the patient is infected with COVID-19 by analyzing only the CT images. The training of the deep learning model occurred with 183 COVID-19 and 146 Non-COVID-19 CTs exams. The methodology presented an F-score of 0.85.

The work presented by Ozkaya et al. [15] uses a technique for merging and classifying COVID-19 deep features. The methodology used a Subset-1 to extract features from 150 CT images. As the expected results were not achieved, a new patch method was tested in a Subset-2 with features fusion. The classification was performed on a Support Vector Machine (SVM), and with pre-trained CNN models, which were used for transfer learning in the proposed method. The method presents promising results for this subset with an accuracy of 98.27%, sensitivity of 98.93%, specificity of 97.60%, precision of 97.63%, F-score of 98.28% and Matthews Correlation Coefficient (MCC) 96.54%.

Wang et al. [16], developed a methodology using deep learning in CT images to classify COVID-19. They used a set of 1,065 CT images, 740 Non-COVID-19 and 325 with COVID-19. Preprocessing was applied to the images in order to extract the region of interest (ROI), and then features were extracted using a modified Inception network. The images were randomly divided into a training and a validation sets. Using internal validation, the methodology has an accuracy of 89.5%, specificity of 88%, and sensitivity of 87%. External tests showed a total accuracy of 79.3%, specificity of 83%, and sensitivity of 67%.

He et al. [4] developed an approach using deep learning to classify COVID-19. They used 746 CT images, 349 with COVID-19 and 397 Non-COVID-19. They were resized to 224×224 and divided into training, validation, and tests sets by patient IDs with a proportion of 60%, 15%, and 25% respectively. The methodology consists of an Auto-Trans, which synergistically integrates self-supervised learning in contrast to the transfer learning to learn representations of features in CT images. The results reach F-score of 85% and AUC of 94%.

As can be seen, the classification of CT exams into COVID-19 and Non-COVID-19 is not a simple task. The use of CNN for feature extraction and classification requires numerous images and training of various parameters to create models. The use of small sets of images can lead to overfitting of the model, having a good performance in the training data but performing poorly in the test data [17]. To solve this problem of poor generalization, Zhao et al. [12], and He et al. [4] used transfer learning; Narin et al. [13] and Ozkaya et al. [15] used pre-trained network models. Also, training this type of network requires considerable time to create a model capable of generalizing efficiently and several tests on architectures and parameters are required. Also, robust machines are needed to run these networks more quickly. However, this is not a trivial task, as it requires numerous tests training the network until satisfactory results are obtained. Thus, we propose the use of CNN for feature extraction in CT images and then, classification with XGBoost. The method showed promising results in the classification of CT images in COVID-19 and Non-COVID-19.

III. Methodology

The proposed method is shown in Figure 1. The methodology consists of: i) acquisition of CT images; ii) extraction of features using CNN; iii) classification of images using XGBoost and iv) validation of results using metrics commonly used in CAD systems.

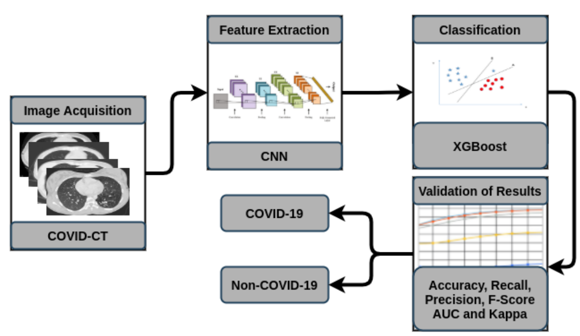

Fig. 1. Proposed methodology.

A. Image acquisition

COVID-CT is a set of CT images developed by Zhao et al. [18] for binary classification of COVID-19. The set consists of 708 CT images, 312 COVID-19 and 396 Non-COVID-19. Figure 2 shows an example of images from COVID-CT. In (a) we have an example of CT with COVID-19 and in (b) we have an example of CT Non-COVID-19.

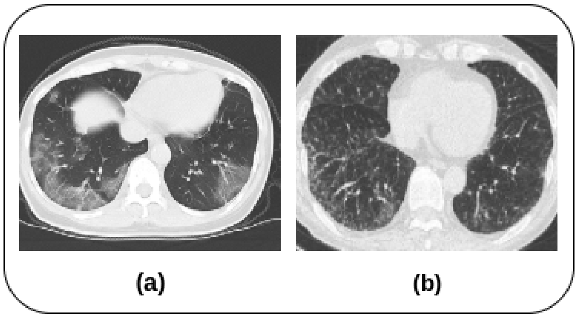

Fig. 2. Example images from COVID-CT, (a) with COVID-19, and (b) Non-COVID-19.

The COVID-CT data set was collected from 760 preprints about COVID-19 from medRxiv, bioRxiv, NEJM, JAMA and Lancet. PyMuPDF 5 was used to extract low-level structure information from the preprinted PDF files. The quality of the images has been preserved. After extracting the information from the structure of the images, the captions associated with the images were identified. The selection of the CT was done manually. Then, the caption or text associated with each CT was read for classification in COVID-19 and Non-COVID-19.

B. Feature extraction

Feature extraction is the most important process in the development of an automatic image classification system [19]. The performance of the classification can be influenced by the quality of the extracted data, leading to a loss of performance by the system. In recent years, deep learning models have been proposed for the feature extraction stage in images. CNN is a model of deep learning that has a hierarchical structure of learning resources with high quality in its layers.

CNN can reduce network complexity and parameter numbers through local receptive fields, sharing operation, and weight sharing. The adjustment of the convolution kernels is done by the backpropagation algorithm [20], which is based on the stochastic gradient descent algorithm, used to reduce the space between the network output data and the training labels. A CNN consists of alternating layers of convolution and subsampling, then transforming into fully connected layers when approaching the output layer.

In this paper, a simplified version of the LeNet-5 network was used to extract characteristics. LeNet-5 is a CNN architecture proposed by Le Cun et al. [21] for handwritten digit recognition. The network structure consists of an input layer (Input), two convolution layers (C1, C2), two subsampling layers (S1, S2), fully connected layers, and an output layer (Output). CNN's structure for feature extraction is shown in Figure 3. Since a convolution operation of the convolution layer can extract only one feature from input feature maps, it requires multiple convolution kernels to extract different features. The input of our CNN is a 128×128 grayscale image. Table I presents a summary of the CNN layers.

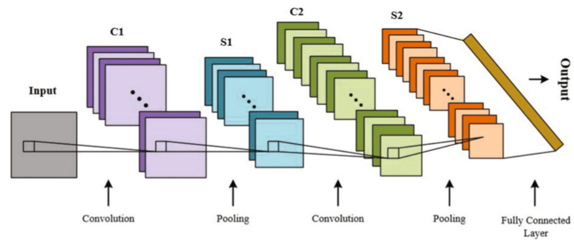

Fig. 3. CNN architecture for feature extraction.

TABLE I
SUMMARY OF CNN LAYERS

Layer	No. of Kernels	Kernel Size	Activation
Input	1	Input Shape	-
Convolution2D	32	5×5	ReLu
Maxpooling2D	-	2×2	-
Convolution2D	32	5×5	ReLu
Maxpooling2D	-	2×2	-
Fully Connected	1024	-	Dropout (0.25)
Fully Connected	2	-	ReLu
SoftMax	-	-	-

To use CNN as a feature extractor, the last fully connected layer of the network was removed and the final output of the new network was used as features that describe the input image. CNN can extract generally useful data features, detect and remove input redundancies and preserve only essential aspects of the data in robust and discriminatory representations [22]. Its semi-connected and fully connected layers provide a reasonable environment for advancing the training and learning process [23]. Thus, the convolution layers serve as an efficient feature extractor, specialized in reducing the size of the data and producing a less redundant data set.

C. Classification

The classification consists of recognizing which of a set of categories a new observation belongs, based on previous training on a data set that has observations whose category is known [24]. In machine learning, tree growth is a highly effective and widely used method. The XGBoost is a scalable and effective machine learning system for tree growth, proposed by Chen et al. [25]. Tree augmentation is a learning algorithm that makes weak classifiers strong in classifying a data set. Let $D = \{(x_i, y_i)\}(|D| = n, x_i \in \mathbb{R}^m, y_i \in \mathbb{R}^n)$ be a database, with n examples and m resources. A $\hat{y}_i$ data augmentation model with K trees input is defined in Equation 1.

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F, \tag{1}$$

where $F = \{f(x) = \omega_q(x)\}(q : \mathbb{R}^m \rightarrow T, \omega \in \mathbb{R}^T$ is the space of the regression or classification trees. Each f_K divides a tree in part q of the structure and part x of the leaf weights. The number of leaves in the tree is represented by T. The f_k functions of the tree model learns by minimizing the objective function, Equation 2.

$$O = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \tag{2}$$

In Equation 2, the distance between the forecast $\hat{y}_i$ and the objective y_i is calculated by the training loss function l. The penalty for the complexity of the tree model is calculated by the term Ω. The use of Equation 2 as an objective function in a tree growth model in Euclidean space, cannot be optimized using traditional methods. The gradient tree boost is an enhanced version of the tree growth, trained in an additive manner, where the prediction of the iteration is $\hat{y}^t = \hat{y}^{t-1} + f_t(x)$. The objective function is changed on the t-th iteration, calculated as in Equation 3.

$$O^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{t-1}) + f_t(x_i) + \Omega(f_t) \tag{3}$$

XGBoost uses the second-order Taylor expansion, with the final objective function in the step t given by Equation 4.

$$O^{(t)} \simeq \tilde{O}^{(t)} = \sum_{i=1}^{n}[l(y_i, \hat{y}_i^{t-1}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t), \tag{4}$$

where g_i e h_i represents first and second order gradient statistics in the loss function, and $\Omega(f) = \gamma T + \frac{1}{2}\lambda||\omega||^2$ in XGBoost. The set of instances of the leaf j given by $I_j = \{i|q(x_i) = j\}$ after removing the constant terms and expanding Ω, can be simplified as in Equation 5.

$$\tilde{O}^{(t)} = \sum_{j=1}^{T}[(\sum_{i \in I_j} g_i)\omega_j + \frac{1}{2}(\sum_{i \in I_j} h_i + \lambda)\omega_j^2] + \gamma T \tag{5}$$

In leaf j, in a fixed tree structure $q(x)$, the weight of solution ω_j^* can be obtained by Equation 6.

$$\omega_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \tag{6}$$

After replacing ω_j^* in Equation 5, we have the Equation 7.

$$\tilde{O}^{(t)} = -\sum_{j=1}^{T} \frac{(\sum_{i \in I_j} g_i)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma T \tag{7}$$

Equation 7 is defined as a scoring function to assess the structure of a tree $q(x)$ and find the ideal structures for classification. This score is similar to the impurity score for evaluating decision trees, except that it is derived for a wide range of objective functions. In practice, it is impossible to search the entire tree structure q. To solve this problem, a greedy algorithm is used that starts from a single leaf and adds branches iteratively to the tree. Supposing that after the division I_L and I_R are the sets of instances of the left and right nodes. Leaving $I = I_L \cup I_R$, the loss reduction after the division is calculated by the Equation 8.

$$O_{split} = \frac{1}{2}\left[\frac{(\sum_{i \in I_L} g_i)^2}{\sum_{i \in I_L} h_i + \lambda} + \frac{(\sum_{i \in I_R} g_i)^2}{\sum_{i \in I_R} h_i + \lambda} - \frac{(\sum_{i \in I} g_i)^2}{\sum_{i \in I} h_i + \lambda}\right] - \gamma \tag{8}$$

This formula is generally used to evaluate divided candidates. XGBoost is a tree method that applies the principle of driving weak learning using descending gradient architecture. However, XGBoost improves the basic structure of Gradient Boosting Machines through system optimization and algorithmic improvements [25]. XGBoost can classify problems using a minimal amount of resources.

D. Validation of results

To validate the model, we used statistical evaluation metrics commonly used in the literature. These metrics are calculated based on the confusion matrix, given the number of true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN), the measures are mathematically expressed as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

$$F - Score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{12}$$

The area under the ROC curve (AUC) is a performance measure for the classification problem in various limit configurations. The AUC represents how much the model can distinguish between classes. By analogy, the higher the AUC, the better the model for distinguishing between patients with and without disease.

The Kappa index measures the agreement between the results presented by the developed methodology and the truth of the human terrain labeled by pathologists. The Kappa value interpretation scale is shown in Table II.

TABLE II
LEVELS OF CLASSIFICATION ACCURACY ACCORDING TO THE KAPPA INDEX.

Índice Kappa (k)	Quality
K $<$ 0.2	Poor
0.2 $\leq$ K $<$ 0.4	Reasonable
0.4 $\leq$ K $<$ 0.6	Good
0.6 $\leq$ K $<$ 0.8	Very good
K $\geq$ 0.8	Excellent

IV. Experiments and results

To extract features from the CNN model, it is need to train the network. First, the input image data is normalized and transferred to the CNN input layer (Table I). After training CNN and updating the weights using the backpropagation algorithm for 200 epochs to obtain an adequate structure for image classification, the XGBoost replaces the CNN output layer and it uses the extracted features for training and testing. The CNN processing time for extract the features is approximately 15 minutes, with a test accuracy of 77.62 and a test loss of 1.12. As our model requires only the features, we can extract features in any intermediate dense layer with the required dimension. For this work, we extracted the features using an intermediate model up to the first fully connected layer. A set of 1,024 features was extracted from each image. After extract the characteristics of the 708 CT images, the classification was performed in COVID-19 and Non-COVID-19 using XGBoost, with cross-validation k-fold, with k = 5. Table III shows the results obtained.

TABLE III
Result using CNN for feature extraction and XGBoost for classification

Accuracy	Recall	Precision	F-Score	AUC	Kappa
95.07	95.09	94.99	95.00	95.00	90.00

The results presented in Table III show that the methodology can efficiently differentiate images with COVID-19 from Non-COVID-19. The methodology obtained accuracy of 95.07% and F-Score of 95%. The kappa index indicates that the methodology is promising for classification, with a value of 90%. The variation of the results presented between the evaluation metrics is very small, showing the efficiency in the categorization. Thus, the features extracted by the proposed CNN model and the XGBoost for classification showed promising in the categorization of images with COVID-19 and Non-COVID-19.

To show that the proposed method is robust, we use the features extracted with CNN, together with classifiers commonly used in the literature. For this test, we used Random Forest and Multi-layer Perceptron classifiers.

- Random forest (RF) is the random combination of multiple decision trees, combined to obtain a more stable and more accurate prediction [26]. The parameters used were: bag size percent = 100, batch size = 100, number of execution slots = 1, max depth = 0 (unlimited), number of randomly chosen attributes = 0, number of iterations to be performed = 100, minimum number of instances per leaf = 1.0, minimum variance for split = 0.001, and random number seed to be used = 1.
- Multi-layer Perceptron (MLP) is a neural network with several layers of neurons connected through weighted synapses, which learns from the backpropagation of the output error and updating the weights [27]. The parameters used in MLP were: learning rate = 0.3, momentum = 0.2, the number of epochs to train through = 500, validation set size = 0 (the network will train for the specified number of epochs), seed = 0, validation threshold = 20, and hidden layers = (number of attributes + classes)/2.

In this experiment, the entire data set extracted with CNN was used for classification, using cross-validation with k-fold, with k = 5. Table IV shows the results obtained.

TABLE IV
Result using features extracted with CNN and traditional classifiers

Clas.	Accuracy	Recall	Precision	F-Score	AUC	Kappa
RF	95.76	**98.05**	**98.05**	**98.00**	**98.00**	**96.10**
MLP	**96.69**	96.68	96.52	96.60	96.60	93.20

The experiments performed in Table IV, show the potential of features extracted using CNN. These results allow us to affirm that XGBoost is promising and that it presents results as promising as traditional methods. We believe that the best parameterization of XGBoost can provide better results.

Table V compares the result obtained with the proposed method with those presented in the works related to the classification of COVID-19. The stage of comparison of results is very complex since many factors can influence a reliable comparison. Thus, we present a summary of the results obtained in the proposed method with those available in related works.

TABLE V
Comparison of the results obtained with the proposed methodology with the related works.

Works	Accuracy	Recall	Precision	F-Score	AUC
[11]	95.12	-	93.36	-	-
[13]	98	96	100	98	-
[12]	84.7	76.2	97.0	85	82.4
[15]	98.27	-	97.63	98.28	-
[16]	89.5	-	-	-	-
[4]	-	-	-	85	94
Our work	**95.07**	**95.09**	**94.99**	**95**	**95**

It can be seen in Table V that the proposed methodology presents very promising results. The proposed methodology achieved an accuracy of 95.07% compared to the results presented by Zhao et al. [12] (84.7%), Wang et al. [16] (89.5%), and He et al. [4]. About the work of Abbas et al. [11] our methodology showed better precision. The work developed by Narin et al. [13] and Ozkaya et al. [15] using pre-trained networks it presented an accuracy of 98% and 98.27% respectively, with our methodology presenting an accuracy of 95.07%. It is worth mentioning that Narin et al. [13] used x-ray images and our methodology used CT. Our methodology does not require much training for feature extraction and the results obtained were close to the best results presented in the related works. The use of CNN to extract characteristics and XGBoost as a classifier showed very efficient results in the categorization of CT images with COVID-19 and Non-COVID-19.

V. Conclusion and Future Work

In this work, we developed an approach to accurately diagnose COVID-19 images from CT scans. The methodology consists of using CNN to extract features from CT images with COVID-19 and Non-COVID-19 and XGBoost for data classification. The methodology showed very efficient results, with an accuracy of 95.07%, recall of 95.09%, precision of 94.99%, F-score of 95%, AUC of 95%, and kappa index of 90%. Thus, the proposed methodology can be used as a computer-aided diagnosis system, providing a second opinion for the specialist in the diagnosis of patients with COVID-19.

Our model can still be improved, as future works, we intend to use larger COVID-19 data sets for the development of a complete methodology using CNN. Also, we intend to test other CNN architectures to extract features from CT images, such as NasNet, ResNet-50, VGG16, and VGG19. Thus, it is intended to obtain a more robust methodology in the diagnosis of COVID-19.

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