ST-based Deep Learning analysis of COVID-19 patients

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Received: August 28, 2021. Revised: May 15, 2022. Accepted: June 17, 2022.
Published: July 27, 2022.

Abstract— The number of deaths worldwide caused by COVID-19 continues to increase and the variants of the virus whose process we do not yet master are aggravating this situation. To deal with this global pandemic, early diagnosis has become important. New investigation methods are needed to improve diagnostic performance. A very large number of patients with COVID-19 have with cardiac arrhythmias often with ST segment elevation or depression on an electrocardiogram. Can ST-segment changes contribute to automatic diagnosis of COVID-19? In this article, we have tried to answer this question.

We propose in this work a method for the automatic identification of COVID patients which exploits in particular the modifications of the ST segment observed on recordings of the ECG signal. Two sources of data allowed the development of the database for this study: 300 ECGs from the "physioNet" database with prior measurement of the ST segments, and 100 paper ECGs of patients from the cardiology department of the hospital X in Tunis registered on (non-covid) topics and covid topics. Four learning algorithms (ANN, CNN-LSTM, Xgboost, Random forest) were then applied on this database. The evaluation results show that CNN-LSTM and Xgboost present better accuracy in terms of classifying covid and non-covid patients with an accuracy rate of 87% and 88.7% respectively.

Keywords— learning, Covid-19, identification, ST segment, ECG, elevation, depression.

I. Introduction

Recently, COVID-19 (Coronavirus 2019) is a respiratory viral pneumonia virus which has a relatively high mortality rate. Because this virus is transmitted very easily and quickly from one person to another and effective therapeutic solutions are not yet available, numerous studies are carried out to search for easily identifiable markers allowing rapid management of the disease. With the rapid increase in the number of suspected cases of this virus, it becomes imperative to help doctors predicting the risks of infection to make the correct decisions. Consequently, several works have been carried out based on the statistics of patients infected with COVID-19. Some research has attempted to find a relationship between the frequency of infection and other factors, such as the prior medical conditions of these patients [1, 2].

Regarding the diagnosis of COVID-19, the clinical examination allows to identify the first symptoms of the disease, which are common fever, fatigue dry cough, loss of adoration, followed by anorexia, myalgia and dyspnea [3]. The clinical examination is supplemented by other exploratory techniques such as electrophysiology and radiography. Radiographic imaging techniques complement the clinical practice very well but have drawbacks: lack of portability, high cost, high radiation exposure, need for skill in image review and analysis. In developed countries, where the pandemic is also raging this type of approach is very expensive and few patients have access to it. New and better-adapted techniques are needed to deal with this scourge, which is intensifying around the world.

The respiratory system has been identified as the primary target of this viral infection, although it also affects other organs in the human body. Especially the cardiovascular system. Recent observations have shown that in addition to symptoms, 90% of patients usually have heart disease. The most common are: acute heart failure, acute coronary syndrome, myocarditis and myopericarditis [4-6]. Considering the advantages of ECG (ElectroCardioGram) based tools such as safety, accessibility, real-time monitoring, reduced cost and automatic detection from ECG is a great added value in diagnosis of this viral virus, in addition to X-ray images and PCR. The ECG signal is therefore very interesting information to use for the rapid management of patients.

In the literature, different cardiovascular alterations in COVID-19 are classified into several categories such as: cardiac arrhythmias, myocarditis and QRST abnormalities [7]. The ECG is not only a standard cardiac signal, but also unique to each individual [8]. Interpretation of computerized ECG is an opportunity to improve accuracy and analysis of COVID-19.

During hospitalization of patients with COVID-19, several anomalies such as Atrial Fibrillation (AF), Tachy-Brady syndrome and acute pericarditis were detected in their ECGs, while rare, RBBB (Right Bundle Branch Block) and

Myocardial Infarction (MI) have been observed in these patients. Li et al. in [9] performed a study examining the ECGs of 113 COVID-19 patients of which 50 of these patients died and the others were cured. They state that ventricular arrhythmia may be statistically significant evidence in patients who died compared to patients who survived. In addition, sinus tachycardia was also observed in the ECGs of COVID-19 patients hospitalized during their study.

According to the literature, ST changes are the most relevant findings in the ECG of COVID-19 patients [10]. Mortality was analyzed for ECG modifications including ST segment elevation, ST segment depression, or T wave inversion that lead to fatal heart attacks [5]. Angeli et al. [11] studied 50 ECGs of suspected COVID-19 patients. They noticed that 30% of patients have ST-T abnormalities and other 30% have left ventricular hypertrophy. In addition, Stefanini et al. [12] showed in their work that ST-segment elevation myocardial infarction is the first clinical manifestation in COVID-19 patients in about 40% of diseased cases. Also, Pranata et al. [13] confirm that ST-segment depression in the ECG of patients may be the first manifestation of this virus.

In another work, Bangalore et al. [14] describe their experiences in New York during the first month of the Covid-19 epidemic. Covid-19 patients who present ST-segment elevation on their ECG were included in the study from six New York hospitals. Whereas, patients with Covid-19 who have non-obstructive disease on coronary angiography or who had normal wall motion on ECG in the absence of angiography were presumed to have non-coronary myocardial injury. In this study, they identified 18 patients with Covid-19 who had ST-segment elevation.

Samely, Payam Dehghani et al. [15] collected a group of 15,000 suspected Covid-19 patients in a global registry (The NACMI Multicenter Registry). These patients frequently present on the ECG recordings with an elevation in their ST segments. Inclusion criteria for participation in this registry are: (1) a positive COVID-19 case, (2) ST-segment elevation or new LBBB on 12-lead ECG during hospitalization, and (3) their ages ≥18 years.

To display that the ST-T change is the most important finding in the abnormal ECG of COVID-19 patients, Wang et al. [16] noticed in 201 of 319 cases that their ECGs were abnormal. In addition, sinus tachycardia, atrial arrhythmia, right bundle branch block (RBBB), sinus bradycardia, atrial fibrillation (AF), and Q and R wave changes occurred in ECGs of COVID -19 patients.

McCullough et al. [17] look in their work if the ECG provides information related to the COVID-19 virus. They reviewed the ECGs of 756 COVID-19 patients to detect several abnormalities such as premature atrial contractions, intraventricular block, repolarization abnormalities. Among these findings, ST segment changes were observed. they deduced that patients with these ECG findings have higher mortality rates.

To find ECG abnormalities, Bertini et al. [18] examined in their study 431 ECGs of patients with COVID-19, of which 93% of patients had cardiac abnormalities. atrial fibrillation was observed in 22% of patients. while in 30% of the patients, an acute right ventricular pressure overload (RVPO) was detected and an elongation of the ST-T segments was observed in the rest of the patients.

The previously presented results in recent research show that the ECG signal represents important information to develop tools for the automatic detection of patients with COVID-19. The ease and affordability of this type of exploration, including in poor regions of the world, justifies the interest of this type of study, which contributes to the rapid management of patients. The cited works have well demonstrated the influence of COVID-19 on the cardiovascular system, but does not present the identification process that would allow their adaptation in personalized health systems.

when health care professionals have no idea about patients' antecedents and cannot make judgments about their conditions without any past experience to guide them and clinical resources (hospital beds, medical mask, ventilator, capacity hospital, etc.) are limited, it is essential to predict which patients will be more likely to develop serious disease.

As studied and presented in Table 1, the Covid identification is done manually. Some of them base their analysis on the ST segments. Thus, we propose, in this work, a new method of automatic identification of COVID patients, to provide healthcare professionals with a decision support tool for the rapid management of COVID patients. This method exploits in particular the modifications of the ST segment in the recording of the ECG signal, which provides several features, providing a set of interesting information to be explored. Indeed, we propose in this work to investigate these parameters by applying a deep learning to the reconstructed database, including healthy subjects (non-COVID) and sick subjects (COVID).

Table 1. Comparative study

References	Covid identification	Use of ST
[9]	Manual	
[11]	Manual	✓
[14]	Manual	✓
[16]	Manual	
[17]	Manual	✓
[18]	Manual	
Our approach	**Deep Learning**	✓

Our contribution consists of:

• Building the database using samples from healthy patients from physioNet and real samples collected by ourselves. Two data sources allowed the development of the database for this study: 300 ECGs from the "physioNet" database with prior measurement of ST segments, and 100 ECG papers of patients from the cardiology department of Hospital X in Tunisia recorded on (non-covid) subjects and covid subjects

• Calculating the slopes of the ST segments of the ECG of the patients and defining significant values for each deformation in the ST (elevation, depression, flat).

• Testing four learning algorithms (ANN, Random Forest, XgBoost, CNN-LSTM) on the built database to identify COVID and non-COVID patients and find the best between them in classifying in these critical cases to facilitate physician diagnosis based on ECG as a method detection of COVID-19.

The rest of the article is divided as follows: The next section discusses the impact of ST segment changes on ECG signal recordings. It also presents the theoretical bases of the automatic classification algorithms based on neural networks that we have exploited in our proposal. Section Ⅲ develops our method, in particular the process of developing the identification parameters. The performance of our suggested contribution is next evaluated and discussed in Section IV. Finally, the conclusions are presented in section V.

II. Background

The ECG is not only a standard cardiac signal but also unique to each individual. Interpretation of computerized electrocardiogram plays a vital role in clinical ECG study. Digital data and the algorithmic paradigm of deep learning offer the possibility to significantly improve the accuracy of ECG analysis. Figure 1 represents the ECG signal and these different waves.

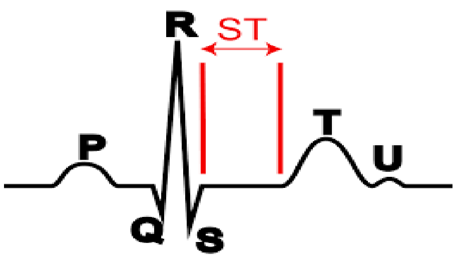


Figure. 1. ECG signal [19]

Table 2 represents the normal values of the durations and amplitudes of the waves described in Figure 1.

Table 2. ECG parameters

Interval	Reason for wave generation	Amplitude	Time interval
P wave	A deflection corresponding to atrial depolarization	Normal amplitude is 1-1.5mm	<0.12 sec
QRS complex	results from the depolarization of the ventricular muscles causing forced contraction of the ventricles	The peak amplitude R range between 8 and 12 mm	<0,04 - 0,10 sec
T wave	this peak represents ventricular repolarization	The normal amplitude varies between 2 and 5 mm	<0,04 - 0,10 sec
U wave	Repolarization of Purkinje fibers	Not measured (low voltage)	<0.01sec

A. The ST segment

The ST segment is a very important, useful and rapid diagnostic tool, which can save a very large number of people with COVID 19 who die every year due to late or incorrect diagnosis caused by human causes. We propose in this work a classification system based on deep learning of ECGs to distinguish COVID and non-COVID patients based on changes in their ST-segment to ensure secure transmission of information to the practitioner to consider, quickly charges COVID patients, and facilitate diagnosis.ST-segment changes detected on ECG area marker of cardiac injury are used as a prognostic indicator in COVID-19 patients [20].

The ST segment is the portion of the ECG that lies between the end of the S wave of the QRS complex and the start of the T wave. It is normally isoelectric (same level as the baseline of the ECG), as shown in Figure 1. The changes, caused by COVID -19 are shown in Figure 2.

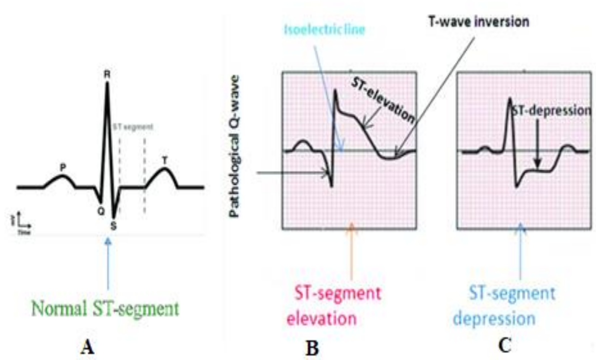


Figure 2. The different forms of ST [21].

Healthy patients show a flat (normal) ST-segment shown in Figure 2.A, while COVID patients show changes such as elevations and depressions.ST-segment elevation refers to an ECG finding in which the trace in the ST segment is abnormally high above baseline [22] as shown in Figure 2.B. The magnitude of this rise is generally greater than or equal to 0.1 millivolts (mv).

Whereas ST depression refers to a finding on the ECG, in which the trace in the ST segment is abnormally low below the baseline [23].

The amplitude of the vacuum is generally greater than 0.05 millivolt (mv). In our approach, the essential parameter related to the ST segments is the slope calculation which will be described in the next section.

B. Used Classification algorithms

We tested four classification algorithms (ANN, Random Forest, XGB, CNN-LSTM) on our database for comparison purposes. These artificial intelligence methods provide a perceptual mechanism independent of the implementer's ideas, and input information to formal logical reasoning, they are optimal from the point of view of execution speed going to a few milliseconds and high precision. The criteria for choosing between learning algorithms are often the speed of convergence or the performance of generalization. We differentiate between algorithms based on precision, learning time and linearity. [24-26].

Artificial Neuron Network. An Artificial Neural Network (ANN) is a collection of nodes called artificial neurons. It represents a computer-based model that models the functioning of a biological brain. Each connection in this model transmits signals for other nodes. Each artificial neuron receives a signal as input, processed to the other neurons. The model is made with a structure composed of input, hidden and output layers [27]. The output of each neuron calculates a weighted sum of its inputs by a nonlinear function and returns a value. This value is used as input to a new layer of neurons or as output as shown in Figure 3. The weight associated with each node increases or decreases the signal strength. It is defined by the learning phase. The signals input pass through the input layers arriving at the output layers several times.

Our ANN model is presented in equation (1) as follows:

$$y = f(b + \sum_{i=1}^{n} x_i w_i) \quad (1)$$

With:

y : Learning output

f : nonlinear function

b : bias vector

x_i : Learning input

w_i: weights

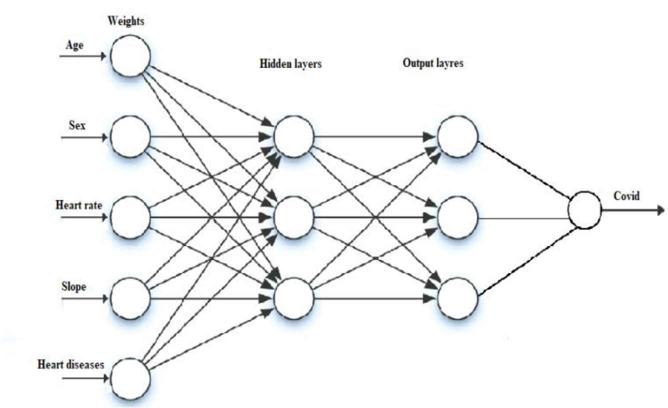


Figure 3. ANN Architecture [27].

Random Forest. The Random Forest Classifier is first introduced by Breiman [28]. It is one of the most recent machine learning techniques. This algorithm is an aggregation of several decision trees, which combines the concepts of random subspaces and bagging. It performs training on multiple trees trained on a slightly different set of data. Each tree is considered as an individual classifier and each classification output is voted on by all decision trees. In our case the inputs the parameters of the patients and the output our class COVID or not. The structure of the random forest is shown in Figure 4.

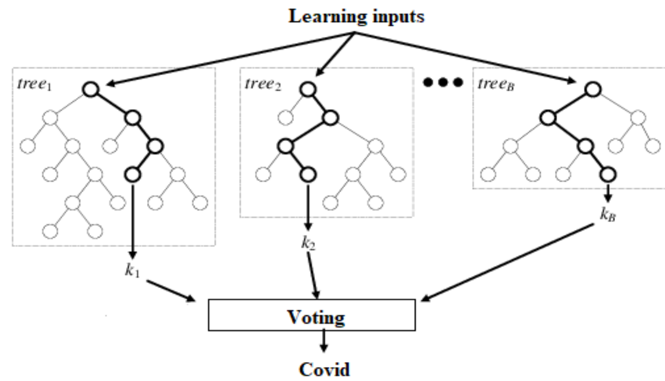


Figure 4. Random Forest Architecture [29]

XGBoost. XGBoost (Extreme Gradient Boosting) is a precise implementation of gradient boosting. It pushes the power limits of boosted tree algorithms and uses machine learning techniques to increase computational speed and yield better results. In this algorithm, the trees are built in parallel, where we use the training data x_i to forecast a target variable $\hat{y}$ [30]. In our case, the x_i are the inputs that make up the patient-related parameters and $\hat{y}$ is the learning output that represents the COVID class. The XGboost architecture is shown in Figure 5.

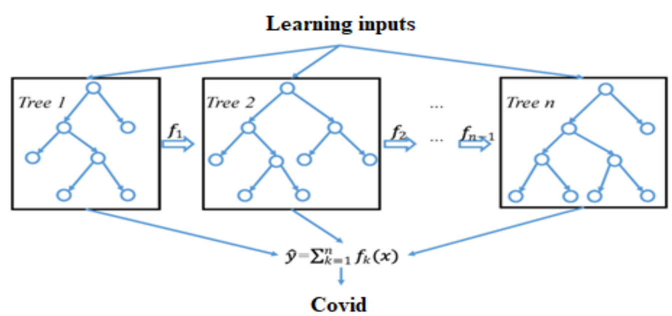


Figure 5. XGBoost Architecture [31].

CNN-LSTM. The CNN-LSTM design implicates the use of convolutional neural network layers for feature extraction on input data connected with LSTM to leverage space-time dependencies. [32]

CNN: Convolutional Neural Networks

Convolutional Neural Networks (CNN) are artificial neural network algorithms based on deep learning. CNN is consisted of an input layer, an output layer and a hidden layer which has several types of convolutional layers: grouping layers, normalization layers and fully connected layers [33]. The convolution and clustering layers extract particular parameters and reduce dimensionality, while the fully connected layers map the retrieved features, which are in our case the patient-related parameters (sex, age, ECG, heart disease) and ST segment slopes to predict a final output that is Covid. In this algorithm, each layer sends its output into the next. In recent years, CNNs have been widely employed to address ECG

DOI: 10.46300/91011.2022.16.39 Volume 16, 2022

classification and detection of cardiovascular disease. The CNN architecture is shown in Figure 6.

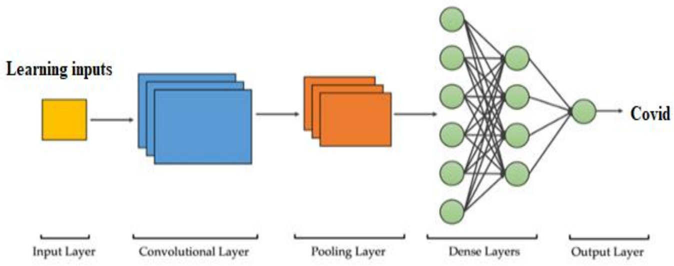


Figure 6. CNN Architecture [33]

LSTM: Long Short-Term Memory

Long-Short-Term Memory (LSTM) units or blocks are an advanced type of recursive neural networks. The main advantage of LSTMs over other kinds of neural networks is their capacity to learn the temporal dynamics of incoming data and selectively recall or forget it [34]. This is done by checking the current state of the memory, which made them popular to classify physiological signals of human body such as in our case ECG.

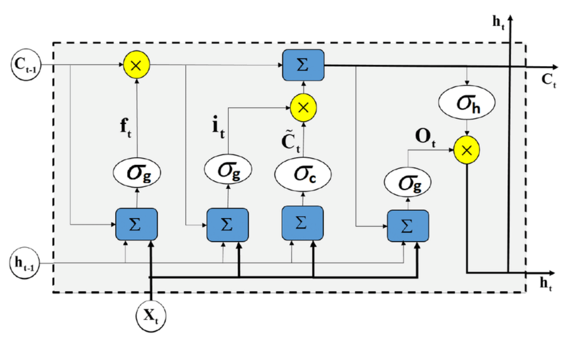


Figure 7. LSTM Architecture [35]

An architecture of an LSTM block generally has a memory cell which is characterized by an entry gate (it), an exit gate (O t) and a forget gate (ft) in addition to the hidden state (ht) in the classic RNN.
The criteria for choosing between these different algorithms are often the speed of convergence or the performance of the generalization. We can differentiate between its algorithms by the precision, the learning time, the linearity. [36-38]. The LSTM architecture is shown in Figure 7.

III. Proposed Solution

Our approach is initially based on the creation of our database and the calculation of the slopes of the ST segments. These parameters are the inputs of our learning algorithms which aim to classify covid and non-covid cases.

Our database is a merger of a physio net database [39] with 300 patients having heart diseases. This dataset gives several variables as well as a target condition to have or not to have heart diseases. This is based on the value of the slopes of the ST segments and 100 real patients collected according to a Tunisian cardiologist of which 60 COVID patients and 40 non-COVID patients represent modifications in their ST segments due to COVID-19.

The used database contains various variables associated to patients, which are:
• Age: age in years
• Gender: 1 = male, 0 = female
• HR: Heart Rate
• Physiological signals linked to the ECG
• Oxygen saturation
•Temperature
• Heart disease (0 = no, 1 = yes)
• Covid (non covid = 0, covid = 1)

Since the ST segment is the most important parameter that determines the cardiovascular disease caused by COVID-19, we calculated the amplitude of the ST segments in the 60 patients in our database of Tunisian patients. The results are illustrated in Table 3.

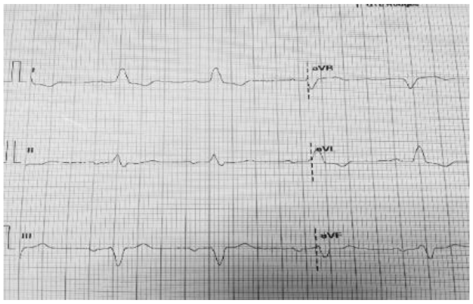
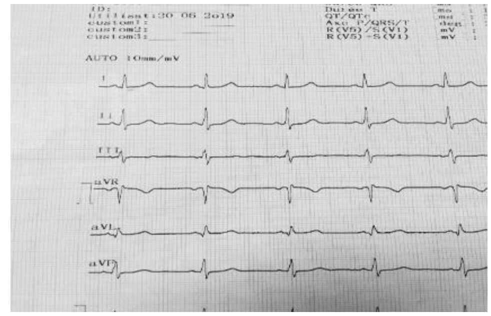
Table.3 Calculation of slopes

Sex /Age	ST-elevation [0.1 mv - 0.2mv]	ST-depression [0.05 mv - 0.2mv]	Flat
Male [28 years -89 years]	12	15	3
Woman [33 years -95 years]	12	16	2

Our database only includes the common entries between these two databases with the calculation of the slopes for the 100 real patients. Table 4 shows examples for three COVID patients with changes in their ST segments.

DOI: 10.46300/91011.2022.16.39

Table.4 Examples of Tunisian COVID patients, exiting in the database.

ST depression	ST elevation	ST Flat
		

A. *Input parameters for learning*

Our classification method is based on well-determined input parameters, which are patients age, Patient's sex, Patient's heart rate, Slope of the ST segment (It is equal to 1 if it is an elevation in the ST segment, is equal to 2 if it is a depression and is equal to 3 if the flat ST segment as described previously), Heart disease (It equals 1 if patient represents heart disease if not equals 0), and the classification output (If it is COVID, it equals 1 if patient COVID, if not equals 0 if patient non-COVID).

B. *Performance metrics*

The performance of a machine learning algorithm is directly related to its ability to predict an outcome. When trying to compare the results of an algorithm with reality, we use a confusion matrix. It assesses the accuracy of a classification system. Each row represents a real class; each column represents a predicted class, represented in equation 2.

$$\text{Cm} = \begin{matrix} TP & FP \\ FN & TN \end{matrix} \qquad (2)$$

Or:

• FN: False Negative represents the number of ECG signals from COVID patients indicating that the class is not COVID or the number of missed detections.

• FP: False Positive indicates the number of ECG signals from non-COVID patients classified as COVID or the number of additional detection peaks.

• TN: True Negative indicates the number of ECGs from non-COVID patients.

• TP: True Positive indicate the number of correctly detected peaks or signals classified as normal.

In our work, the suggested learning algorithms aim to classify patients into two categories, COVID and non-COVID, in order to facilitate the diagnosis of their condition. For this, we

use a reliable algorithm that displays precise values in order to make an accurate medical diagnosis. Therefore, Accuracy (Acc) is the most important metric that influences the performance of learning algorithms, to correctly classify ECG signals in the database, this metric represents the fraction of total right forecasts. represented in equation (3).

$$Acc = \frac{(TN+TP)}{(\text{TP+TN+FN+FP})} \qquad (3)$$

IV. Results and Discussion

In our work, we used various learning algorithms (ANN, XgBoost, Random Forest, CNN-LSTM) to determine which one was the best for our case study. In our contribution, we vary the learning rate to indicate the speed at which the coefficients in our algorithms evolve. We have chosen at the beginning 20% as a learning rate until arriving at a maximum rate is equal to 80% as presented in the figures of the results. This variation allows us to see their influence on accuracy, which indicates the performance of the used learning algorithms and on the confusion matrix which is used to determine whether or not there is a faulty categorization in the learning. These algorithms were developed using anaconda Navigator, which is based on Python 3 and all of our simulations are executed on an Intel Core i5 PC. The samples used during training for the training and test data sets are stored on our machine.

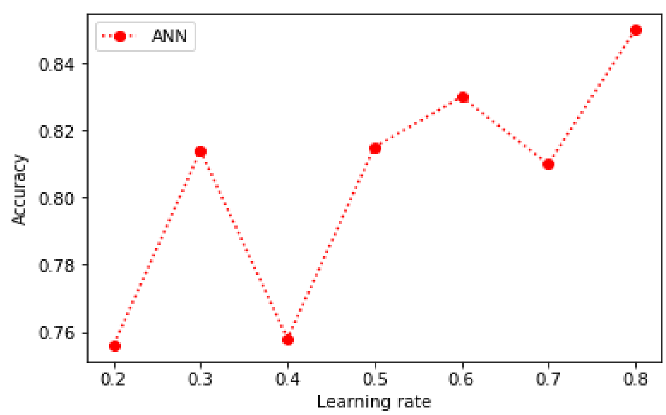


Figure 8. Accuracy variation as a function of learning rate for ANN

As shown in Figure 8, When the learning rate is equal to 0.8, the ANN achieves its maximum accuracy of 0.83 (83%), which confirms the high performance of neural networks when increasing the system learning rate.

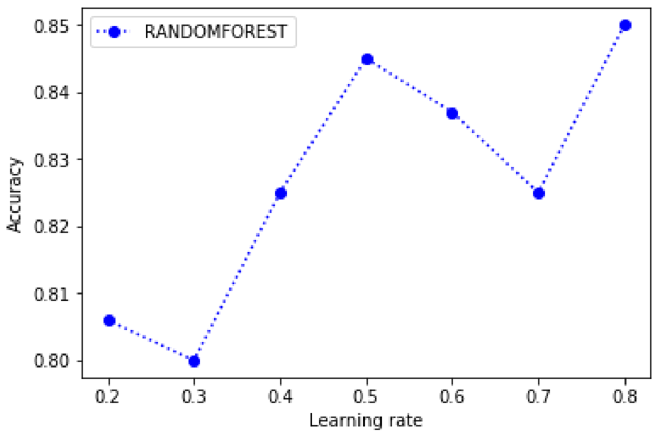


Figure 9. Accuracy variation as a function of learning rate for RANDOM FORERST.

The Random Forest algorithm reaches its maximum precision value of 0.85 (85%), when the learning rate is 0.8 (80%). As shown in Figure 9.

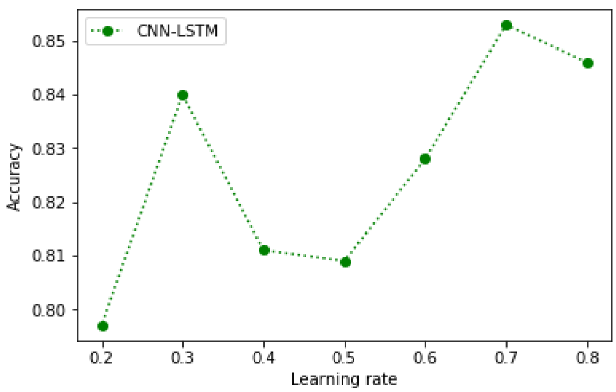


Figure 10. Accuracy variation as a function of learning rate for CNN-LSTM.

As shown in Figure 10. CNN-LSTM reaches its maximum accuracy value of 0.87 (87%), when the learning rate is 0.7 (70%).

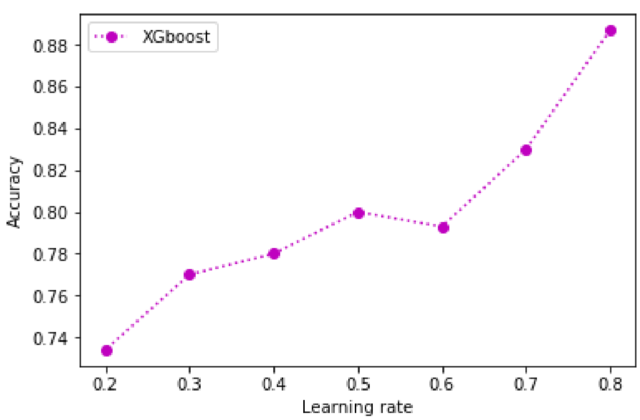


Figure 11. Accuracy variation as a function of learning rate for XGboost.

XGboost reaches its maximum accuracy value of 0.887 (88.7%), when the learn rate is 0.8 (80%).We have found that CNN-LSTM and XGboost have the best performance in the detection of the covid cases. As shown in Figure 11.

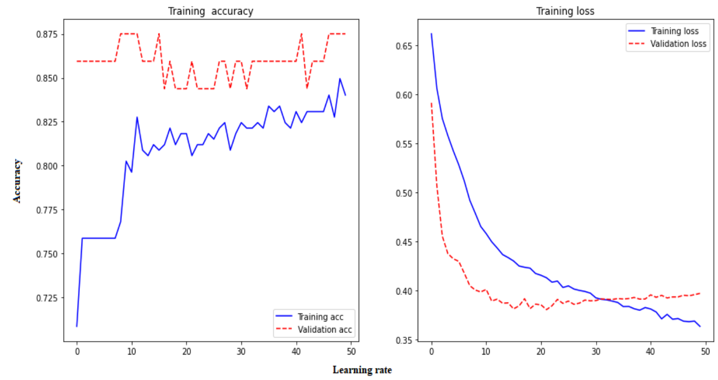


Figure 12. Accuracy variation and training loss as a function of learning rate (CNN-LSTM)

The value of the loss is a metric that implies how badly or well our model behaves after each iteration. We notice that this value decreases with the increase in learning rate while the accuracy increases with the increase in learning rate as shown in Figure 12. This confirms that the CNN-LSTM has good and efficient results in our classification case compared to the used learning algorithms.

Indeed, we compared the confusion matrices for a learning rate equal to **20%**, as shown in Table 5.

Table 5. Confusion matrices.

Algorithms	ANN	RANDOM FOREST	CNN-LSTM	XGBOOST
Matrices of confusion	$Cm = \begin{matrix} 60 & 2 \\ \mathbf{12} & 6 \end{matrix}$	$Cm = \begin{matrix} 58 & 2 \\ \mathbf{10} & 10 \end{matrix}$	$Cm = \begin{matrix} 60 & 0 \\ \mathbf{20} & 0 \end{matrix}$	$Cm = \begin{matrix} 61 & 3 \\ \mathbf{6} & 10 \end{matrix}$

As shown in Table 5, the bold value of FN indicates the number of ECG signals from COVID patients indicating that the class is not COVID. This is the most important parameter in medical learning, i.e. the algorithm is more efficient when FN decreases. We notice that XGboost is the more efficient than the tested algorithms with **FN = 6** for a learning rate equal to **20%.**

V. Conclusion

The COVID-19 virus causes a high-fatality respiratory illness that requires easy-to-reach markers for prediction. In this work, we built our test database using samples from non-COVID patients from physioNet, as well as real samples collected by ourselves that include COVID patients. Then, we calculated the slopes of the ST segments of the ECG patients. Then, we compare between four classification algorithms namely (ANN, CNN-LSTM, XgBoost, Random Forest) in order to choose the best performing one. These algorithms are based on the evaluation of ST segments and other physiological parameters of patients collected from their ECG data. The results on real ECG data show that the CNN-LSTM and XGboost models perform better than other methods. In our case, they have an accuracy rate of 87% and 88.7%, respectively. Therefore, the exploitation of the ECG by these two methods will allow anticipating the decisions to better diagnose patients by the coronavirus covid-19.

This work is a preliminary study because our database does not include enough COVID patients, but the identification of this virus from ST segments is a useful new approach that makes it easier for healthcare professionals to detect COVID-19 early from ECG, especially for urban areas like Tunisia.

Some research says that COVID-19 is not the primary cause of these cardiovascular issues, however it should be emphasized that it can disclose or worsen the underlying diseases.

In the future, we plan to use a large database of Covid patients, other parameters related to this virus and apply other learning algorithms to improve our approach. Thus, we conceive of seeing the influence of treatments taken during confinement on the ECGs of COVID patients and the risk of triggering other diseases.

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