COVID-19 Detection Based on ECG Processing

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The World Health Organization (WHO) has been on alert since early 2020 regarding the Coronavirus Disease 19 (COVID-19). With well over 6 million deaths worldwide, the scientific community is developing new ways to detect the disease. As one of the most used clinical examination methods, it is of great importance to study the changes in the electrocardiographic (ECG) activity, as well as to understand the ECG features related to COVID-19.

Keywords: COVID-19 ; artificial intelligence ; signal processing ; image processing ; computerized diagnostic systems

1. Introduction

1.1. Mechanism

COVID-19 is a disease caused by a Severe Acute Respiratory Syndrome-Coronavirus-2 (SARS-CoV-2) [1], which is a single, positive-strand Ribonucleic acid (RNA) virus that causes severe respiratory syndrome in humans. SARS-CoV-2 belongs to the family Coronaviridae and is divided into alpha (α-CoV), beta (β-CoV), gamma (γ-CoV), and delta (δ-CoV) coronaviruses. It was initially detected in bats, and the first cases of the disease were detected in a market in China. For this particular case, SARS-CoV-2 is a coronavirus genetically similar to β-CoV which, similar to α-CoV, can infect mammals [2][3][4].

SARS-CoV-2 uses Angiotensin Converting Enzyme 2 (ACE2), which is a receptor in the cell surface, to start the infection. After the binding of the spike protein with the ACE2 receptor, the invasion process is triggered by host cell proteases. The virus releases the RNA into the host cell, then the RNA is translated into viral replicase polyproteins. The negative RNA copies of the viral genome are produced by the enzyme replicase using the positive RNA genome. During transcription, RNA polymerase produces a series of subgenomic mRNAs and translates them into viral proteins. The RNA genome is assembled into virions in Golgi and Endoplasmic Reticulum (ER), which bud into the ERGIC (ER–Golgi intermediate compartment) and are released out of the cell [2][3][4].

SARS-CoV-2 uses ACE2 to initiate the infection process. This receptor is present in the kidney, blood vessels, heart, and the lungs, which means it can cause respiratory, cardiovascular, gastrointestinal, and central nervous system diseases [2][3][4].

In the next section, the most frequent symptoms identified in COVID-19 patients, as well as eventual complications, are briefly presented.

1.2. Symptoms

COVID-19 patients may present mild to severe symptoms, with a substantial portion of the population not demonstrating any type of symptoms. The reported symptoms include fever, cough, and shortness of breath. A small segment of the population presented some gastrointestinal symptoms such as vomiting, diarrhea, and pain in the abdominal area [3][4].

Cardiovascular complications have been reported in COVID-19 patients as well. The reports have described acute cardiac injury, cardiogenic shock, electrocardiographic (ECG) changes, right ventricular dysfunction, thromboembolic complications, and tachyarrhythmias [5].

1.3. Laboratory Diagnostic

Diagnosing active cases of COVID-19 is one of the most important tasks for controlling the pandemic. Laboratory testing techniques have been developed to obtain an accurate diagnosis of COVID-19. The most common techniques are Nucleic Acid Amplification Test (NAAT) and Antigen detection [3][6].

NAAT is a technology used to diagnose an active COVID-19 infection by the use of Real-Time Polymerase Chain Reaction (RT-PCR) assay to detect SARS-CoV-2 RNA from the upper respiratory tract [3][6].

Antigen detection tests are tests used to detect the presence of SARS-CoV-2 viral proteins. Most of the available antigen kits require samples taken from the nasal cavity or nasopharynx, with some kits allowing samples from saliva as well [6].

2. COVID-19 Detection Based on ECG Processing

Most of the impact of COVID-19 is focused on the respiratory system, but the virus can also cause a variety of cardiac complications, including myocardial injury, heart failure, cardiogenic shock, and cardiac arrhythmias, which shows the importance of ECG [7][8].

ECG is an exam that can monitor the electrical activity of the heart. In the early cases of COVID-19, myocardial Injury was found in patients that were infected with the virus [9].

As one of the most used clinical examination methods, it is of great importance to study the changes in the electrocardiographic activity, as well as to understand the ECG features related to COVID-19 [10].

In a study done in 2020 by Bergamaschi et al. [9], 269 patients were admitted with COVID-19. The ECGs were made at the admission date and after 1 week from hospitalization. The authors evaluated the correlation between ECGs findings and major adverse events (MAE). The study concluded that abnormal ECG at hospitalization and elevated baseline Troponin values were more common in patients who developed MAE. Other studies [10][11][12][13][14] concluded that Troponin is a good indicator to access the severity of the infection and the ECG might be an easy tool for risk stratification in such patients. In the same year, another study done by Angeli et al. [15] concluded that the evolution of ECG abnormalities is independent of the severity of pulmonary tract infection and reflects a wide spectrum of cardiovascular complications.

Looking into the ECG abnormalities, several studies found that the S-T segment alteration was the most frequent ECG finding and signs of left ventricular hypertrophy were associated with a worse prognosis [1][10][13][14], concluding that abnormal T wave or the presence of S-T segment elevation/depression can have a good prognostic in predicting the mortality of COVID-19 patients [10][13][14].

A study carried out by Bassiouni et al. [16] created several deep learning models and classifiers to distinguish COVID-19 from other cardiovascular diseases (CVDs) and Control, having the best Accuracy result of 99.74% with the ECGConvnet being used as a classifier. The ECGConvnet was the proposed system used in this study and it demonstrated that it is possible to develop an automatic diagnosis system for COVID-19 based on deep learning using ECG images.

A study [17] done in 2022 aimed to automatically utilize ECG signals to detect COVID-19. The ECG signal was obtained from ECG paper records, then the electrocardiographic signal was entered as input into a one-dimensional convolutional neural network (1D-CNN), and the authors tried to correctly diagnose the pathologies present in the database. The investigators separated the database into three different classes: COVID-19, Normal, and Other. The Other class contained the diseases myocardial infarction (MI), abnormal heartbeats, and recovered myocardial infarction (RMI). The investigation obtained an Accuracy of 83.17%, an F1-score of 85.38%, a Sensitivity of 84.81%, and a Specificity of 86.28% when using the three classes at the same time as the target.

Another study [18] submitted in 2022 approached the automatic detection of COVID-19 by utilizing models of Convolutional Neural Networks (CNN). The investigators tested the CNN pre-trained models ResNet50, DenseNet-201, VGG16, VGG19, Inceptionv3, and Inceptionresnetv2. ECG pre-processing was performed to eliminate undesirable distortions. Then, a data augmentation technique was implemented as a way to artificially inflate the dataset before entering the CNN models, and from all the models tested in this study, the VGG16 model had the best result of Accuracy with 81.39% for a target containing Normal ECGs and COVID-19 patients.

Attallah [19] investigated the use of Bi-Layers of deep features integration to diagnose COVID-19 based on ECG images. The paper used a methodology with four stages: preprocessing, feature extraction and integration, feature selection, and classification. The features were extracted from the last average pooling layer and the last fully connected layer from some pre-trained CNNs, which were the ResNet-50, the DenseNet-201, the Inception-V3, Xception, and the Inception-ResNet. The study concluded with 98.80% Accuracy, 98.8% Specificity, and a Sensitivity of 98.8% when doing a Binary classification between Normal ECGs and COVID-19 ECGs. The Multi-class Classification, which was the same class as the Binary plus Abnormal ECGs, had 91.73% Accuracy, 91.80% F1-Score, 95.9% Specificity, and 91.7% Sensitivity.

Sobahi et al. [20] published an article in 2022 that demonstrated an ECG-based COVID-19 detection. The investigators approached the situation with the use of an attention-based 3D CNN model with residual connections (RC). The database that was used contained 12-lead ECG printouts and was distributed between three classes: normal subjects, COVID-19 patients, and patients with abnormal heartbeat (AHB). The CNN model was comprised of 19 layers: 1 image 3D input, 3 3D convolution layers, 3 batch normalization layers, 3 rectified linear unit (ReLu) layers, 2 dropout layers, 2 additional layers, 1 Sigmoid layer, 1 Elementwise Multiplication layer, a fully connected layer, a softmax and classification layers. The study concluded with a Binary Classification (COVID-19 patients vs. Normal subjects) Accuracy of 99% and a Multiclass Classification (Covid patients vs. Normal subjects vs. Abnormal Heartbeat patients) Accuracy of 92%.

An investigation [21] published in 2022 considered a public dataset containing ECG images to diagnose COVID-19. Inside the database, there were five distinct categories, such as normal, COVID-19, MI, AHB, and RMI. They tested six different CNN models as a way to distinguish COVID-19 from the other types of classes. The models were ResNet18, ResNet50, ResNet101, InceptionV3, DenseNet201, and MobileNetv2. The investigators used six different classes: normal, COVID-19, MI, AHB, RMI, and CVDs. They also visualized three different classification schemes: a Binary classification between the normal class and the COVID-19 class, a three-class classification between the normal class, the COVID-19 class, and the CVDs class, and a five-class classification between the normal class, the COVID-19 class, the MI class, the AHB class, and the RMI class. For the Binary classification, the best result was 99.1% Accuracy, for the three-class classification the best Accuracy result was 97.36%, and for the five-class classification the best Accuracy was 97.83%.

Even though COVID-19 is, for the most part, a respiratory or lung disease, the cardiac system can also suffer significant damage. One common complaint of COVID-19 patients is the appearance of palpitations or even the rise of symptoms similar to a heart attack, which includes chest pain, shortness of breath, and Echocardiogram changes [22].

A non-invasive method such as the biomarker Heart Rate Variability (HRV) is a way to assess the Autonomic Nervous System (ANS) activity as an interaction between the respiratory, cardiovascular, and nervous systems, which means that it can be another possible way of studying the difference between COVID-19 and non-COVID-19 patients [23].

A study done by Mishra et al. [24], in 2020 took advantage of the heart rate sensors present on wearable devices. The authors found that elevated resting heart rates and outlying HR/steps measurements were altered, usually in advance of the symptoms.

A study [25] published in 2021 used a methodology in which the data was collected through a smartphone camera using photoplethysmography technology, wrist-worn smartwatches, and wrist-worn bands synchronized with a smartphone app. The investigators used three different classes: Before COVID-19, during COVID-19, and after COVID-19 for patients that used the smartphone app and were positive for the disease. They concluded that there was no statistically significant interaction between the HRV indicators before, during, and after COVID-19 illness. However, they found statistical differences in the standard deviation of normal-to-normal intervals (SDNN) and root mean square of successive normal-to-normal interval differences (RMSSD) for some patients.

Another study done by Hasty et al. [26] compared the levels of C-reactive protein (CRP), which is a marker of systemic inflammation, associated with severe disease in bacterial or viral infections [27], with the SDNN. In this experiment, they used patients that presented hypoxic respiratory failure requiring high-flow nasal cannula or mechanical ventilation, and the experiment was done for seven days. The study concluded that there was a drop of more than 40% in the standard deviation of the interval between heartbeats (SDNN) followed by more than a tripling of CRP in the 72 h that followed.

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