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## Research Article

**Keywords:** COVID-19, ECG, Paper-based ECG, GLCM, Hexaxial Mapping, Deep Learning, Convolutional Neural Network, Diagnosis

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# Classification of COVID-19 electrocardiograms by using hexaxial feature mapping and deep learning

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## Abstract

**Background:** Coronavirus disease 2019 (COVID-19) has become a pandemic since its first appearance in late 2019. Deaths caused by COVID-19 are still increasing day by day and early diagnosis has become crucial. Since current diagnostic methods have many disadvantages, new investigations are needed to improve the performance of diagnosis.

**Methods:** A novel method is proposed to automatically diagnose COVID-19 by using Electrocardiogram (ECG) data with deep learning for the first time. Moreover, a new and effective method called hexaxial feature mapping is proposed to represent 12-lead ECG to 2D colorful images. Gray-Level Co-Occurrence Matrix (GLCM) method is used to extract features and generate hexaxial mapping images. These generated images are then fed into a new Convolutional Neural Network (CNN) architecture to diagnose COVID-19.

**Results:** Two different classification scenarios are conducted on a publicly available paper-based ECG image dataset to reveal the diagnostic capability and performance of the proposed approach. In the first scenario, ECG data labeled as COVID-19 and No-Findings (normal) are classified to evaluate COVID-19 classification ability. According to results, the proposed approach provides encouraging COVID-19 detection performance with an accuracy of 96.20% and F1-Score of 96.30%. In the second scenario, ECG data labeled as Negative (normal, abnormal, and myocardial infarction) and Positive (COVID-19) are classified to evaluate COVID-19 diagnostic ability. The experimental results demonstrated that the proposed approach provides satisfactory COVID-19 prediction performance with an accuracy of 93.00% and F1-Score of 93.20%. Furthermore, different experimental studies are conducted to evaluate the robustness of the proposed approach.

**Conclusion:** Automatic detection of cardiovascular changes caused by COVID-19 can be possible with a deep learning framework through ECG data. This not only proves the presence of cardiovascular changes caused by COVID-19 but also reveals that ECG can potentially be used in the diagnosis of COVID-19. We believe the proposed study may provide a crucial decision-making system for healthcare professionals.

**Source Code:** All source codes are made publicly available at:

<https://github.com/mkfzdmr/COVID-19-ECG-Classification>

**Keywords:** COVID-19; ECG; Paper-based ECG; GLCM; Hexaxial Mapping; Deep Learning; Convolutional Neural Network; Diagnosis

## 1 Background

2 Coronavirus Disease 2019 (COVID-19), caused by  
3 the novel coronavirus severe acute respiratory syn-  
4 drome coronavirus 2 (SARS-CoV-2), first emerged in  
5 the Wuhan region of China in early December 2019.  
6 COVID-19 is a contagious virus that causes respira-  
7 tory tract infection and can be transmitted from per-  
8 son to person and it has continued to spread since its  
9 first appearance and caused a pandemic that still con-  
10 tinues around the world [1, 2]. It has been affecting  
11 life negatively in terms of health, economy, and social  
12 aspects [3]. As of March 3, 2020, the global mortality  
13 rate is 3.4%. As of March 24, 2021, there are more than  
14 123 million confirmed cases. Over 100 million people  
15 have recovered, while more than 2.71 million patients  
16 died due to the virus [4]. Fast and accurate diagno-  
17 sis of the disease is of great importance in this pro-  
18 cess. For this reason, various protocols for the diagno-  
19 sis of the disease have been announced by the World  
20 Health Organization (WHO). Today, the most widely  
21 used standard test method for diagnosing COVID-19  
22 is real-time reverse transcriptase-polymerase chain re-  
23 action (rRT-PCR). Although PCR tests are the gold  
24 standard due to the high accuracy rate (sensitivity),  
25 they require long waiting times before results (at least  
26 4 to 6 hours), experienced personnel, and a logistically  
27 central location [5]. Other tests and diagnostic meth-  
28 ods that can produce faster results are still under in-  
29 vestigation. One of the methods used for the diagnosis  
30 of COVID-19 is radiography images. Due to the dis-  
31 advantages of the PCR technique, chest radiography  
32 images such as computed tomography (CT) and X-ray  
33 are frequently used for the early diagnosis of COVID-  
34 19 [6]. These images contain useful information for the  
35 diagnostic step. Several studies have found changes in

radiographic images that were taken before COVID-19  
symptoms began [7].

In the fight against COVID-19, Internet of Things  
(IoT) applications provide great benefits from diag-  
nosis to treatment of the disease [8, 9]. Recent stud-  
ies suggest to integrate artificial intelligence (AI) into  
IoT, Industry 4.0, and Industry 5.0 applications to aid  
healthcare professionals and patients [10–13]. Diagno-  
sis and treatment with AI are frequently used in the  
field of medicine and it is a helpful tool for clinicians.  
Deep learning, one of the sub-branches of AI, creates  
an end-to-end model without the need for manual fea-  
ture extraction step compared to traditional machine  
learning methods and it is popularly used in many  
areas today. As a result of the rapid spread of the  
COVID-19 pandemic in the world, there are situa-  
tions where the number of healthcare professionals is  
insufficient. Due to all these conditions and other dis-  
advantages, interest in AI-based automatic diagnosis  
systems is increasing day by day. Deep learning meth-  
ods have the potential to provide timely assistance to  
patients with the fast and automatic diagnosis of the  
disease. These methods do not require expertise and  
therefore they can help healthcare professionals [14].

Many studies have used radiographic images for the  
diagnosis of COVID-19. Ozturk et al. [14] used X-ray  
images as input for the deep learning model to di-  
agnose COVID-19 automatically. In the DarkCovid-  
Net model with 17 convolutional layers, they achieved  
98.08% accuracy in binary classification (COVID, No-  
Findings) and 87.02% accuracy in multiclass classifi-  
cation (COVID, No-Findings, Pneumonia) by using  
the real-time classifier. Toğaçar et al. [15] proposed  
a model using X-ray images preprocessed with Fuzzy  
Color for COVID-19 detection via deep learning. They  
classified the features extracted with MobileNet2 and  
SqueezeNet using support vector machines (SVM).  
They achieved 99.72% overall accuracy as a result

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of multiple classifications (COVID, No-Finding, Pneumonia). Karaknis et al. [16] proposed architecture to create synthetic images to increase the limited number of X-ray images. In their study, with two deep learning models, they used binary classification for COVID-19 and normal cases, and multi-class classification for COVID-19, normal cases, and pneumonia. In the study, the lightweight deep learning model is presented as an alternative to ResNet8. They obtained 98.7% accuracy, 100% sensitivity, and 98.3% specificity for binary classification, and 98.3% accuracy, 99.3% sensitivity, and 98.1% specificity for multi-class classification. For further studies using X-ray and CT images for automatic detection, the reader is referred to the accompanying paper [17]. However, besides the high success rate in diagnosing COVID 19, radiographic imaging techniques have some disadvantages such as not being portable, high cost, large radiation exposure, requiring technical skill for image analysis, and examination [18]. New techniques are needed as the COVID-19 pandemic continues.

While the primary impact area of COVID-19 infection is the respiratory system, it also affects multiple human body systems, especially the cardiovascular system [19]. The cardiovascular changes in COVID-19 patients [20–24] have prompted an investigation of the diagnostic value of the electrocardiogram (ECG). In the literature, many types of cardiovascular changes in COVID-19 which can be classified as cardiac arrhythmias, QRST abnormalities, myocarditis and pericarditis, and conduction disorders were reported [25]. The most important finding in ECGs of COVID-19 patients is the ST changes [21, 22, 26–31]. Shortening of the PR interval [29, 32] and changes such as QT prolongation [33–37] were also observed in the ECG of COVID-19 patients. It should be noted that some studies claim that COVID-19 cannot be considered the complete cause of these cardiovascular complications,

but it should be emphasized that it can reveal the underlying conditions or worsen them [25].

Considering the published studies, ECG can be used to evaluate mortality, intubation, and intensive care unit entry rates beyond patients with severe disease. In order to propose ECG as a diagnostic assessment of COVID-19, ECGs of the moderate and asymptomatic patients need to be analyzed. Recently, a research group has published a publicly available dataset containing paper-based ECG of normal (no cardiac findings), cardiac and COVID-19 patients, which provides an opportunity to succeed in the proposed aim. Considering the advantages of ECG application such as low cost, harmlessness, accessibility, and real-time monitoring, automatic detection from ECG may be of great value in COVID-19 diagnosis besides radiography images and PCR. In the previous researches, no studies have been found in which deep learning or even AI is applied using ECG data to the diagnosis of COVID-19, to the best of our knowledge.

Additionally, many deep learning approaches were proposed for automatic cardiac arrhythmia detection. Besides using 1D ECG signals [38, 39] to train the deep network, in many studies were used a 2D representation of 1D ECG signals like ECG time-amplitude images [40, 41], time-frequency representations by using Short-Time Fourier Transform (STFT) [42, 43] and Continuous Wavelet Transform (CWT) [44], higher-order spectral representations [45], and dual beat coupling matrices [46] in order to train CNN architecture. Considering the wide usage of paper-based ECG reports [47], there is a lack in the automatic detection of cardiac problems which require special attention.

In the light of these findings, this study addresses two different problems:

- Automatic classification of the disorders that may occur in ECG due to COVID-19 and even automatic diagnosis of COVID-19 through ECG data.

- In cases where ECG data can be collected in the form of paper-based reports instead of digital ECG signals, proposing a novel and effective method that can aid automatic diagnosis from printed paper-based ECG reports.

For these purposes, a novel, low-cost, and efficient automatic COVID-19 diagnosis method is proposed for the first time using deep learning and hexaxial feature mapping with ECG data in this study. Firstly, paper-based ECG images obtained from the publicly available database are pre-processed and segmented. Then a novel hexaxial feature mapping process is implemented to generate hexaxial ECG images. These hexaxial ECG images are trained with a new deep network architecture to diagnose COVID-19.

In the following, this paper is structured as; in the [Related works](#) section, related papers investigating cardiac findings that may be caused by COVID-19 are summarized; in the [Methods](#) section, firstly, the used dataset is explained, then the segmentation and pre-processing of the paper-based ECG images, feature extraction step, ECG mapping process, and finally the proposed deep network architecture are examined in detail; in the [Results and discussion](#) section, the classification results are presented, and findings and limitations are discussed; and finally in the [Conclusion](#) section, the main findings of the study are summarized and some useful suggestions are given.

## Related works

In this section, the changes seen in ECG associated with COVID-19 are detailed with the studies in this field. Wang et al. [33] detected abnormal ECG in 201 of 319 COVID-19 patients and they reveal that ST-T change is the most important clinical evidence in the abnormal ECG. In addition, sinus tachycardia, atrial arrhythmia, right bundle branch block (RBBB), sinus bradycardia, atrial fibrillation (AF), atrial tachycardia, abnormal Q-wave, and weak R-wave progres-

sion were also observed in the ECG of patients with COVID-19. In the comparative statistical analysis between patients with and without the severe disease, a significant difference was found in all complications. A significance of  $p < 0.001$  was achieved in the ST-T change. Pavri et al. [32] tried to detect heartbeat and PR changes from the ECG of 75 COVID-19 patients. In 50.7% of patients with COVID-19, it was observed that the PR interval shortened with the acceleration of the heart rate. In addition, no change was observed in 49.3% of COVID-19 patients. In the statistical analysis performed with ECGs taken before COVID-19 and during COVID-19, a significant difference was found between the two groups in their heart rate and PR interval. In the conducted study, the mortality rate was found to be higher in patients with shortened PR interval. Angeli et al. [48] examined the ECGs of 50 patients with COVID-19. They found ST-T abnormality in 30% of the patients and left ventricular hypertrophy in 30%. Also, various abnormalities such as AF, tachy-brady syndrome, and acute pericarditis have been detected in the ECG of patients with COVID-19 during hospitalization. Although rare, RBBB and Myocardial Infarction (MI) have been observed in patients with COVID-19. Li et al. [49] conducted a study by examining the ECG of 113 COVID-19 patients 50 of whom died and 63 of whom survived. Ventricular arrhythmia was found to be statistically significant evidence in patients who died compared to patients who survived. In addition, sinus tachycardia was observed widely in the ECG of patients with COVID-19. Santoro et al. [34] detected QT prolongation in 14% of the patients in their study, by examining the ECG of 110 patients with COVID-19. Jain et al. [35] reported that the drugs used for the treatment of COVID-19 caused QT prolongation in the ECG. To test this situation, the ECG of 2006 COVID-19 patients was examined. According to the obtained

1 results, QT prolongation was detected in 19.7% of pa-  
2 tients with COVID-19. In addition, it was determined  
3 that patients with this abnormality in their ECGs had  
4 higher rates of intubation and intensive care unit entry  
5 than others. McCullough et al. [50] evaluated whether  
6 the ECG provides prognostic information in COVID-  
7 19 disease. In their study, they examined the ECG of  
8 756 patients with COVID-19 and detected abnormali-  
9 ties such as atrial premature contractions, intraventric-  
10 ular block, repolarization abnormalities, and RBBB  
11 were detected. Among these findings, ST-elevation was  
12 rarely observed. And it was stated that patients with  
13 these ECG findings had higher mortality rates. Lam  
14 et al. [29] conducted a study with 18 COVID-19 pa-  
15 tients. They detected abnormalities including PR de-  
16 pression, biphasic T-waves, PR prolongation, Q-waves,  
17 ST-segment elevation, atrial flutter, RBBB, and atrial  
18 trigeminy in 63% of the patients. According to their re-  
19 sults, it was determined that COVID-19 patients with  
20 abnormal ECG tended to have increased severity and  
21 stay in the hospital for 61% longer than other patients.  
22 Bertini et al. [30] examined the ECG of 431 patients  
23 with COVID-19. They found abnormalities in the ECG  
24 of 93% of the patients. AF was observed in the ECG  
25 of 22% of patients. Acute right ventricular pressure  
26 overload (RVPO) was detected in 30%, and ST-T pro-  
27 longation was observed in 4 patients. Nemati et al.  
28 [51] suggested that ECG could be an early indicator  
29 for COVID-19 infection this is because the changes  
30 in the ECG were also observed in COVID-19 patients  
31 without any cardiovascular history. As detailed above,  
32 many studies have demonstrated that some cardiac  
33 disorders may be caused by COVID-19 and they can  
34 be easily observed in ECG. Also, many cardiovascu-  
35 lar changes continue to be associated with COVID-19  
36 infection day by day. Therefore, ECG can be an im-  
37 portant diagnostic tool not only for the early diagnosis  
38 of COVID-19 but also for the cardiovascular complica-

tions which may arise during or after COVID-19 dis-  
ease for mild patients.

## Methods

This study consists of 5 main stages. The visualizations  
of these stages are shown in Figure 1.

### COVID-19 ECG images dataset

In this study, a publicly available dataset containing  
ECG images of cardiac and COVID-19 patients has  
been used. The dataset was shared online by Khan  
et al. [52] from the University of Management and  
Technology on Mendeley Data. The dataset includes  
1937 distinct patients' paper-based ECG report im-  
ages. ECG reports were examined by experts and the  
images consist of 250 COVID-19 patients, 77 MI pa-  
tients, 548 patients with abnormal heartbeats (recov-  
ered from COVID-19 or MI), 203 patients that have  
MI history, and 859 people without any cardiac find-  
ings. The presented dataset is the first dataset shared  
for the ECG of COVID-19 disease, in fact, it is the  
first COVID-19 bio-signal database as far as we know.

The paper-based ECG records in the dataset consist  
of ECG signal drawings from a 12-lead system (I, II,  
III, aVR, aVL, aVF, V1, V2, V3, V4, V5, and V6) and  
the sampling rate was 500 Hz. As understood from the  
paper-based ECG reports, ECG signals were collected  
via EDAN SE-3 series 3-channel electrocardiograph,  
and some of the signals were applied with a 0.67-25  
Hz bandpass filter, and some of them with a 0.5-100  
Hz bandpass filter and a 50 Hz notch filter.

Unfortunately, the images of the dataset have some  
limitations. The images do not have sufficient resolu-  
tion, and report image sizes are not standard. In par-  
ticular, the ECG reports of COVID-19 patients consist  
of different types of reports. Other reports are more  
standardized and have better resolution.

In this study, two different classification problems  
are discussed; (i) to distinguish COVID-19 from No-

1 Findings (that have normal ECG); all 250 COVID-19  
2 and 250 out of 859 normal paper-based ECG report  
3 images were used and *(ii) to diagnose* COVID-19  
4 (COVID-19 (Positive) vs other types of ECGs (Neg-  
5 ative)); all 250 COVID-19, 83 of 859 normal, 83 of  
6 548 abnormal heartbeat and 84 of 280 MI paper-based  
7 ECG report images were used. The reason for choosing  
8 the equal amount of data in the classification process  
9 is to eliminate the imbalanced dataset effect. In addi-  
10 tion, all paper-based ECG report images used in this  
11 study were selected from the group in which the 0.67-  
12 25 Hz bandpass filter was applied. An example for a  
13 12-lead paper-based ECG report of a COVID-19 pa-  
14 tient from the dataset (Report number: 211) is shown  
15 in [Figure 1](#).

#### 16 Pre-processing and segmentation

17 In this section, the conversion of noised 12-lead paper-  
18 based ECG images to noiseless channel-based binary  
19 images is explained. There are many studies that digi-  
20 tize paper-based ECG images [53, 54]. Nevertheless,  
21 these studies have high computational costs. More-  
22 over, the complex image processing and digitization  
23 processes may cause degeneration of ECG signals and  
24 cause information loss. Therefore, in this study, a sim-  
25 ple and effective paper-based ECG segmentation ap-  
26 proach that does not require any complex image pro-  
27 cessing method is proposed. Moreover, the proposed  
28 method does not involve a digitization process and pre-  
29 serves the ECG signals as images. Hence, no degrada-  
30 tion occurs in ECG signals. In the proposed method,  
31 the quality of ECG images depends only on the sam-  
32 pling rate of paper-based ECG signals.

33 For this purpose, firstly, the part containing each  
34 ECG channel is segmented from paper-based ECG im-  
35 ages. The segmentation process was carried out with  
36 a rectangular frame. Since the paper-based ECG im-  
37 ages in the dataset have different resolutions, the po-  
38 sitions of this frame on the paper-based ECG image

were measured manually. The segmentation process  
is performed to include one or more RR intervals in  
each channel. An example of a segmented paper-based  
ECG image is shown in [Figure 2a](#). Segmented ECG-  
channel images have a background sourced from the  
ECG-paper lines. This background is removed within  
two steps. In the first step, the background lines were  
removed by filtering the input densities with a density  
mapping function [55], because the background has  
denser or softer RGB values than the curves expressing  
the ECG signal. This is essentially a contrast enhance-  
ment process. An example of a segmented paper-based  
ECG image with no background lines is shown in [Fig-  
ure 2b](#). Unfortunately, the obtained images still include  
traces of the background where the background lines  
are as dense as ECG curves. Besides, since only the  
signal pattern in ECG reflects the information about  
the heartbeat period, the RGB color distribution of  
ECG curves is negligible [41]. For this reason, the RGB  
images obtained in the last stage were converted to  
binary images by taking the “G” channel as a refer-  
ence (since “G” channel information is not domi-  
nant in paper-based ECG images due to the nature  
of ECG paper). An example of the paper-based ECG  
image obtained after the binarization process is shown  
in [Figure 2c](#). While the ECG curve consists of adja-  
cent interconnected pixels, background noise is sepa-  
rate from this curve as seen in [Figure 2c](#). In the second  
step, the interconnected ECG curve pixels are filtered  
from background noises by using the *bwareafilt* func-  
tion of MATLAB<sup>®</sup>. Thus, the eventual binary seg-  
mented paper-based ECG image was obtained without  
any loss. An example of the final image is shown in [Fig-  
ure 2d](#). The pre-processed and segmented paper-based  
ECG image database is available at [GitHub](#).

#### GLCM and feature extraction

Feature extraction and selection play an important  
role in machine learning-based classification problems.

1 A set of images can be categorized according to their  
 2 most distinctive features which can be found by imple-  
 3 menting an appropriate feature extraction method. In  
 4 our approach, at the end of the pre-processing steps,  
 5 all paper-based ECG images were converted to binary  
 6 images where the ECG signal is represented by 0s. We  
 7 chose the Gray Level Co-Occurrence Matrix (GLCM)  
 8 method [56] for feature extraction because it has been  
 9 shown that GLCM is very useful in extracting the im-  
 10 portant properties of an ECG signal such as periodicity  
 11 and distortions [57, 58].

12 GLCM generates a square matrix whose dimension  
 13 equals the number of gray levels in the image. Each  
 14 cell of GLCM corresponds to the number of the co-  
 15 occurring related gray levels in the image. The GLCM  
 16 matrix  $G$  can be calculated from the equation (1) as  
 given in [58]:

$$G_{\Delta x, \Delta y}(i, j) = \sum_{x=1}^N \sum_{y=1}^M \begin{cases} 1, & I(x, y) = i \quad \& \\ & I(x + \Delta x, y + \Delta y) = j \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

17  
 18 where  $I$  is the image of the pre-processed binary ECG  
 19 images with dimension  $N \times M$ ;  $i$  and  $j$  are the pixel  
 20 values,  $x$  and  $y$  are the spatial positions in the image  
 21  $I$ .  $\Delta x$  and  $\Delta y$  are the spatial offset, and  $I(x, y)$  is the  
 22 pixel value. In our problem, the pixel values  $i, j$  take  
 23 0, 1 and  $G$  is a size of  $2 \times 2$  matrix. Taking the offset  $\Delta x$   
 24 and  $\Delta y$  values as 1 and 0, respectively, the transitions  
 25 between the pixel with 0 and 1 intensities in horizon-  
 26 tal direction provide the amount of deterioration in  
 27 the signal specially in its periodicity. The second-order  
 28 statistical analysis of the GLCM matrix provides dif-  
 29 ferent parameters that are widely evaluated as image  
 30 features in image classification studies [59].

31 In this work, we extracted the most commonly used  
 32 four GLCM features which are energy, contrast, cor-  
 33 relation, and homogeneity from each lead of the seg-

mented binary ECG images. Mentioned features can  
 be calculated using the  $G$  matrix obtaining in equa-  
 tion (1) as follows:

$$\begin{aligned} \text{Energy}(E) &= \sum_{i=0}^1 \sum_{j=0}^1 p_{ij}^2 \\ \text{Contrast} &= \sum_{i=0}^1 \sum_{j=0}^1 (i-j)^2 p_{ij} \\ \text{Homogeneity} &= \sum_{i=0}^1 \sum_{j=0}^1 \frac{1}{1+(i-j)^2} p_{ij} \\ \text{Correlation} &= \sum_{i=0}^1 \sum_{j=0}^1 \frac{(i-\mu_i)(j-\mu_j)}{\sigma_i \sigma_j} p_{ij} \end{aligned} \quad (2)$$

where  $p_{ij}$  is the probability of adjacent pixels that have  
 $ij$  intensity pattern and it is stored in the GLCM ma-  
 trix  $G$ , i.e. for a binary image first element of  $G$  shows  
 the probability of co-occurrence 00 pattern in the im-  
 age  $I$ .  $\mu_i, \mu_j, \sigma_i$ , and  $\sigma_j$  are means and standard de-  
 viations of the intensities, and were given as follows:

$$\begin{aligned} \mu_i &= \sum_{i=0}^1 \sum_{j=0}^1 i p_{ij} & \sigma_i &= \sqrt{\sum_{i=0}^1 \sum_{j=0}^1 (i-\mu_i)^2 p_{ij}} \\ \mu_j &= \sum_{i=0}^1 \sum_{j=0}^1 j p_{ij} & \sigma_j &= \sqrt{\sum_{i=0}^1 \sum_{j=0}^1 (j-\mu_j)^2 p_{ij}} \end{aligned} \quad (3)$$

We assessed the four GLCM features from a statisti-  
 cal perspective in order to select the most informative  
 and distinctive feature to represent the binary ECG  
 images. We performed the one-way ANOVA test on  
 GLCM features obtained from the binary ECG images.  
 ANOVA test results of GLCM features that belong to  
 No-Findings and COVID-19 classes are given in Fig-  
 ure 3. We found that all GLCM features were statisti-  
 cally significant relative to each other ( $p < 0.0001$ ).  
 When the gray level pixel distribution of an image is  
 periodic or homogeneous, the energy value is expected  
 to converge to the upper limit [60]. We concluded that  
 it is prominent to use GLCM energy among the other  
 GLCM features to emphasize the periodicity relation

between RR intervals in ECG images. In addition, the energy values are directly related to uniformity. As explained in the [Related works](#) section, since the periodicity and orderliness of COVID-19 ECG images are expected to be different from the ECG images without COVID-19, it has become important to measure image uniformity. Moreover, GLCM energy values help determine disorders in texture [61] which may be related to COVID-19. Although all GLCM features that are obtained are statistically significant, for the reasons explained above, the GLCM energy is chosen as a feature to be used in the mapping process.

### Hexaxial feature mapping

Inspired by our previous study [62], we proposed a novel method to represent the paper-based ECG record as a colorful two-dimensional image for various deep learning applications. The feature mapping approach can be defined as assigning a specific value to a specific point in a two-dimensional space. The point here is the projection of the measurement location in three-dimensional space into two-dimensional space (which we call the image plane in our study). The value is the feature that represents the measured signal in the related measurement point, i.e. the GLCM energy of binary ECG images of each lead. We used the hexaxial diagram of heart's electrical axis [63] as the image plane to define the measurement points.

Our method relies on the 12-lead ECG record system which is accepted as the gold standard for ECG diagnosis, and works with the logic of combining Einthoven, Goldberger, and Wilson derivation systems [64]. In [Figure 4a](#), 6 limb leads (blue arrows) (I, II, III, aVR, aVL, aVF), their reversed polarities (-I, -II, -III, -aVR, -aVL, -aVF), and 6 precordial leads (red arrows) (V1, V2, V3, V4, V5, V6) are shown. In ECG analysis, the projection of six limb leads with their negative poles on the coronal plane is called a hexaxial reference system shown by the blue points in [Figure 4b](#). In this

presentation, lead I is selected as the zero reference point and lead I and aVF intersect at a right angle at the electric center of the heart. The precordial leads have lied on the transverse plane and only the positive pole of each lead is indicated by the end labels shown by the red points in [Figure 4b](#). It is assumed that the Lead V6 is parallel to Lead I and the other precordial leads must be placed with a phase angle from V6 in the transverse plane. The leads V2 and V6 intersect at approximately a right angle at the electrical center of the heart [65]. The phase angles of all leads are given in [Figure 4b](#).

According to this configuration, the heart is assumed to be placed at the origin of a 3D cartesian coordinate  $(x, y, z)$  system with axis Lead I (or V6) as  $y$ , aVF as  $-z$  and V2 as  $x$ . Lead I and aVF span the coronal plane whereas V6 and V2 span the transverse plane. To find measurement points of all leads in 3D space, we assume that the endpoints of each limb leads lie on a circle centered at the origin with a radius  $r$  in the image plane, and the endpoint of precordial leads lie on a semi-circle centered at the origin with a radius  $r$  in the transverse plane. The measurement points of the **limb leads** are already in the image plane and they can be calculated easily using these transforms:

$$\begin{aligned} x &= 0 \\ y &= r \cos \theta \\ z &= r \sin \theta \end{aligned} \tag{4}$$

where  $\theta$  denotes the given phase angles of the leads. The measurement points of the **precordial leads** lie on the  $x-y$  plane and can be projected onto the image plane by using these transforms:

$$\begin{aligned} x &= 0 \\ y &= r \cos \theta \\ z &= 0 \end{aligned} \tag{5}$$

As a result, 18 measurement points are defined in 2D cartesian coordinate ( $y - z$ ) system. The virtual measurement points and their placement in the image plane are shown in Figure 4b.

The next step in the hexaxial feature mapping method is assigning a value to the measurement point that represents the measured signal. The hexaxial feature mapping procedure can be defined as follows:

$$HFM(y_{lead}, z_{lead}) = \begin{cases} E(I_{lead}), & \text{lead} = \text{I,II,III,} \\ & \text{aVR,aVL,aVF,} \\ & \text{V1,V2,V3,V4,V5,V6} \\ E(\bar{I}_{lead}), & \text{lead} = \text{-I,-II,-III,} \\ & \text{-aVR,-aVL,-aVF} \end{cases} \quad (6)$$

where  $y, z$  shows the location of the projected measurement points of the leads, and  $E$  indicates the normalized GLCM energy (Energy values rescaled between 0 and 1 to avoid inconsistency and bias).  $HFM$  is an expression of the value of  $E$  at location  $y, z$ . The  $HFM$  of the positive poles of limb leads and the precordial leads are found by calculating the GLCM energy of binary ECG images denoted by  $I$ . To find the  $HFM$  of the negative poles, the images of corresponding positive poles are vertically mirrored denoted by  $\bar{I}$  then the GLCM energy is computed.

As a result, the GLCM energy features of each lead are mapped onto the coronal plane using virtual measurement points in the 2D plane. A natural two-dimensional neighbor interpolation process [66] is carried out between the existing measurement points to generate a smooth 2D colorful image. In Figure 4c (no cardiac findings) and Figure 4d (COVID-19) RGB color representation of the hexaxial feature mapping images are shown. When these two images are compared, it can be seen that the hexaxial feature mapping method has succeeded in representing the ECG of a healthy person in a distinguishing way from the ECG of COVID-19 patients. Furthermore, the proposed ap-

proach not only provides a 2D image representation for deep learning studies but also collects all 12-lead ECG information into a single image. Thus, the information contained in the multi-channel ECG can be analyzed and processed over a single image. Since the proposed approach includes the derivation information of 12-lead ECG, hexaxial mapping images also contain the electrical axis activity of the heart.

### Proposed deep learning architecture

Recently, Convolutional Neural Network (CNN) architectures have become incredibly popular in image classification, object detection, and segmentation. A typical CNN architecture consists of a convolutional layer, a pooling layer, and a fully connected layer, respectively. The CNN architecture aims to obtain deep features. The convolutional layer scans the inputs via a filter and obtains feature maps. The pooling layer provides the selection of more meaningful features to reduce the computational cost. And finally, the fully connected layer flattens the inputs and calculates the probabilities of the labels. There are many CNN architectures proposed for image classification consisting of the combination of these layers. Designing a model inspired by previously proven CNN models is more efficient than rebuilding a new architecture [14].

In recent studies, various approaches were conducted on the selection of deep network architecture [14, 16, 67, 68]. Ardakani et al. [69] trained 10-different CNN architectures and emphasized the network which had the best classification performance among trained models. In [67], ResNet-50 is selected as a base model due to it yielded the best classification performance. In this study, two main criteria were considered to build the deep model; computational complexity and classification performance. For this purpose, hexaxial feature mapping images were trained with the network architectures which are suggested by recent state-of-the-art studies. When the classification results are

1 compared ResNet-50 [70], AlexNet [71], ResNet-8 [16],  
2 and SqueezeNet [72] yielded an accuracy of 73.65%,  
3 93.60%, 85.12%, and 92.52%, respectively. The re-  
4 sults revealed that AlexNet which has less network  
5 depth achieved significant accuracy compared to well-  
6 known architectures. Additionally, the AlexNet model  
7 was presented, it was used to classify about 1.2 mil-  
8 lion images in 1000 different classes. Besides, AlexNet  
9 used the Dropout method to overcome overfitting and  
10 Rectified Linear Units (ReLU) as the activation func-  
11 tion to shorten the training time. Also, the model  
12 was compatible with multiple GPUs. Due to these  
13 advantages, AlexNet achieved the best performance  
14 in ImageNet Large Scale Visual Recognition Chal-  
15 lenge in 2012 (ILSVRC2012) [71]. Further, AlexNet  
16 has achieved effective performance in many ECG clas-  
17 sification studies [45, 73]. Therefore, a new deep net-  
18 work architecture modified from the AlexNet model is  
19 designed in this work. Graphical representation of the  
20 proposed CNN architecture is shown in Figure 5.

21 In the designing phase, we build a 9-layer model  
22 that contains one more convolutional layer with 256  
23 filters and  $(3 \times 3)$  kernel size compared to the original  
24 AlexNet. Therefore, the input shapes require a larger  
25 size of  $256 \times 256$  compared to AlexNet. Moreover, in-  
26 put images with larger size need to resize, and the  
27 padding process is performed on input images that  
28 have lower size. In order to avoid increasing the train-  
29 ing cost, the number of layers is not increased further.  
30 Initially, the high-resolution 300 DPI colorful hexaxial  
31 feature mapping images are resized to  $256 \times 256 \times 3$   
32 to feed the proposed CNN architecture. This resizing  
33 process also provides less training cost and a balanced  
34 kernel size. In the first two layers, the input images  
35 are passed through a convolutional layer and a pooling  
36 layer. While both layers perform a convolution (Conv)  
37 with a  $(11 \times 11)$  kernel and using a ReLU function as  
38 the activation function in the convolutional layer, the

first one has a stride of 4 and the second one has a  
stride of 2. Both pooling layers (maximum) used in this  
step have a kernel size of  $(2 \times 2)$  and a stride of 2. The  
next stage consists of four repetitive convolutional lay-  
ers called as a convolutional block. Each convolutional  
layer has  $(3 \times 3)$  kernels and a stride of 1, and the num-  
bers of filters are 96, 256, 256, and 128, respectively.  
Following the convolutional block is a maximum pool-  
ing layer with  $(2 \times 2)$  kernel size and a stride of 2. In  
the next step, after the model is flattened, there is a  
dense block consisting of three fully connected layers.  
The dropout method (drop rate of 0.4) is used to pre-  
vent overfitting after each fully connected layer in the  
dense block. And finally, the SoftMax function is used  
as the binary classifier in the output layer. The pro-  
posed CNN architecture has over 23.5 million trainable  
parameters. Also, in Figure 5 the output dimensions  
of the network layers are illustrated.

During the training phase of the proposed archi-  
tecture, Adam Optimizer [74] was used, because of  
its effective choice of hyperparameters. Moreover, the  
batch size is fine-tuned with parameter tuning. Differ-  
ent batch sizes (32, 64, 128, and 256) have been tested  
in the training phase to achieve the least error rate, and  
the batch size optimized to 128. Furthermore, different  
learning rates (0.01, 0.001, 0.0001, and 0.00001) were  
tested to ensure a lower error rate and to prevent sat-  
uration of the model. Although decreasing the learn-  
ing rate hyperparameter slightly increased the training  
cost, it fine-tuned on 0.0001 to avoid local minimums.  
Epochs are tuned at 200 to observe the robustness of  
the models and to compare the test results with equal  
conditions.

## Results and discussion

In this study, the generated images based on hexaxial  
feature mapping, explained in the Methods section, are  
used to train our proposed architecture. All training,  
validating, and testing phases are performed on a com-

puter with Nvidia GeForce RTX 2080 TI GPU and 64 GB RAM using Tensor Flow 2.2 and Cuda 10.1.

Modified stratified k-fold cross-validation is adopted to evaluate the robustness of the proposed models in this study. Cross-validation methods are used to evaluate the robustness of models during the training phase. The stratified k-fold cross-validation process re-arranges the dataset to ensure each fold properly represents the entire dataset. We added an extra validation step to the stratified k-fold cross-validation to construct modified stratified k-fold cross-validation which is visualized in Figure 6. The training phase is processed as follows; firstly, the dataset is shuffled and then split k-part by using the stratified k-fold. While the k-1 part is used to train the model, the remaining one k-part is used in the testing phase and cover all classes without overlap. After the test and training data sets are separated, the remaining training set is split again with a training and validation split process (split rate of 0.25). We chose k as 5 in our study. Considering there are a total of 500 hexaxial mapping images in each phase, 100 images are used in each test phase and any of them are not included in training phase (whereas, the total number of data is 9000 when training 2D ECG spectral images (*18-lead x 250 paper-based ECG reports x 2 groups*)). The data used in the test phase cover two classes (COVID-19 vs others) with approximately equal amounts of data. The validation data (consisting of 100 images) is used both in the training and validating phases. Thus, a two-step verification process is performed to evaluate the robustness of the models during the training and testing phases. Furthermore, recall (REC), precision (PRE), accuracy (ACC), specificity (SPE), F1-Score (F1-S) [15], area under the receiver operating characteristic curve (ROC-AUC) [62, 75], and mean squared error (MSE) [17] are calculated during the validating

and testing phases to investigate the robustness of the models.

### Experimental results and implications

We performed four experiments on two different binary classification problems. All experiments were carried out with 5 repetitive folds by using modified stratified k-fold cross-validation scheme. In the first stage (*i*), we trained three different models *to detect and classify* COVID-19. At this stage, we aimed to evaluate the performance of the proposed architecture and to show the effect of the proposed hexaxial feature mapping process on the success of the classification. For comparison, we trained the AlexNet architecture using ECG hexaxial mapping images (Experiment 1), the proposed architecture using ECG hexaxial mapping images (Experiment 2), and finally the proposed architecture using 2D ECG spectral images (Experiment 3). In the second stage (*ii*), we trained our proposed model *to predict and diagnose* COVID-19 (Experiment 4). At this stage, we aimed to evaluate the diagnostic value of ECG by distinguishing ECG disorders caused by COVID-19 from other ECGs without COVID-19 findings and diagnose COVID-19 through ECG data. The classification results of all test phases are given in Table 1.

**Experiment 1:** By training the AlexNet architecture using hexaxial mapping images, an average of 93.60% ACC value was achieved. The best training performance was achieved with 95.00% ACC in the 5<sup>th</sup> fold and 2<sup>nd</sup> fold. Test ACC values have a standard deviation of  $\mp 2.63\%$ . The deviations of ACC changes in each fold are within acceptable limits. Also, the average PRE, REC, SPE, F1-S, and ROC-AUC values were yielded 91.67%, 96.00%, 91.20%, 93.7%, and 97.48%, respectively. The average test loss was calculated as 0.453 and the average MSE was calculated as 0.064. The obtained REC values were equal or higher than SPE values in all folds. This situation implied that the

1 false-positive rate (FPR) was higher than the false-  
2 negative rate (FNR). FPR indicates the rate of being  
3 marked to have COVID-19, while the individuals did  
4 not have COVID-19. It took an average of 101.98 sec  
5 to train AlexNet using hexaxial mapping images.

6 **Experiment 2:** By training the proposed architec-  
7 ture using hexaxial mapping images, an average of  
8 96.20% ACC value was achieved. This average ACC  
9 value provided a 2.60% better performance compared  
10 to AlexNet. The proposed model exhibited an ACC  
11 performance of over 96.00% on all folds, and the best  
12 performance was at the 4<sup>th</sup> fold with an ACC value  
13 of 98.00%. ACC values obtained in the test phase had  
14 only  $\mp 1.48\%$  standard deviation. This situation was  
15 an indicator of the robustness of the model. Moreover,  
16 the average PRE, REC, SPE, F1-S, and ROC-AUC  
17 values were achieved 96.20%, 94.33%, 98.40%, 94.00%,  
18 96.30%, and 99.15%, respectively, and where all val-  
19 ues performed better than AlexNet in all cases. The  
20 test loss proved the robustness of the model with a  
21 small value of 0.292 and a very low MSE of 0.038.  
22 By using the proposed architecture, the training time  
23 of hexaxial mapping images took only an average of  
24 103.21 sec. An almost ideal classification success has  
25 been achieved in Fold-4 with a ROC-AUC value of  
26 99.88%. Similar to the training of AlexNet, FPR val-  
27 ues were higher than FNR values. The achieved success  
28 in all folds of the proposed method has provided a sig-  
29 nificant improvement compared to the AlexNet. Fur-  
30 thermore, although the proposed architecture included  
31 more layers compared to AlexNet, an average training  
32 time difference was only 1.23 sec. Therefore, we used  
33 the proposed architecture to train other models.

34 **Experiment 3:** In this step, we trained our pro-  
35 posed model with 2D ECG spectral images and evalu-  
36 ated the results to observe the success of the proposed  
37 hexaxial mapping approach. In this step segmented  
38 and pre-processed 2D ECG spectral images were given

directly to the deep network as an input. All 18-lead (6  
of them augmented) ECG images of each patient were  
used in the training phase in order to include the in-  
formation of all ECG channels. There was no evidence  
that the abnormalities in ECG caused by COVID-19  
can be separated on a channel basis. All findings in  
the studies summarized in the [Related works](#) section  
have been observed on the entire ECG, and as far as  
we know, no channel-based study has been conducted.  
Consequently, at each training, validation, and testing  
phase 7200, 1800, and 1800 2D ECG spectral images  
were used. As seen in [Table 1](#), by training the pro-  
posed architecture with the 2D ECG spectral images,  
an average of 81.08% ACC was yielded. The highest  
ACC value was calculated as 84.83% at the 1<sup>st</sup> fold and  
ACC values had a standard deviation of  $\mp 2.82\%$ . The  
highest standard deviation occurred at this step. More-  
over, the lowest average PRE, REC, SPE, F1-S, and  
ROC-AUC values were calculated as 79.42%, 84.10%,  
77.81%, 81.68%, and 89.82%, respectively in this step.  
The average test loss was 0.644 and the MSE was 0.220  
and was relatively higher than other trained models.  
Especially, SPE had the lowest value with 77.81%. Due  
to the increasing training size, the computational cost  
had increased and the average training time was calcu-  
lated as 528.43 sec. A significant difference of 15.12%  
ACC was observed compared to training of hexaxial  
mapping images. As a result, the hexaxial mapping ap-  
proach achieved higher performance with less compu-  
tational cost and training time compared to the train-  
ing of 2D ECG spectral images.

70 **Experiment 4:** To predict COVID-19 from ECG,  
71 two groups were generated Positive vs Negative. While  
72 the Positive group consisted of only the ECG data  
73 of COVID-19 patients, we included an approximately  
74 equal amount of normal ECG (of individuals without  
75 any cardiac findings), history of MI patients' ECG, and  
76 abnormal ECG (of patients recovered from COVID-19

or MI) to the Negative group. Firstly, we analyzed the GLCM energy features of both groups statistically by applying a one-way ANOVA test and it verified that the GLCM energy values of COVID-19 ECGs were statistically significantly different from the GLCM energy values of the normal, MI, and abnormal ECGs groups ( $p < 0.0001$ ). The ANOVA results are shown in the [Figure 7](#). In order to evaluate the success of our proposed hexaxial mapping approach in this classification problem, mapping images that belongs to Positive and Negative groups were trained with the proposed architecture. As seen in [Table 1](#), an average of 93.00% ACC value was achieved with the proposed method and the best ACC value was obtained as 95.00% at the 2<sup>nd</sup> fold. Test ACC values had a standard deviation of  $\mp 1.58\%$ . Moreover, with the proposed approach, the average PRE, REC, SPE, F1-S, and ROC-AUC values were achieved 90.58%, 96.00%, 90.00%, 93.20%, and 94.98%, respectively. Although the average test loss was relatively high (0.628), the MSE value was quite low (0.070). As with other trained models, the FPR value was higher than the FNR value. It took an average of 103.92 sec to train the proposed model with the proposed approach.

As mentioned above, the classification of COVID-19 ECG data with the proposed method has yielded outstanding test performance. Further, in [Figure 8](#) training and validation ACC graphs and training and validation loss graphs are shown for all folds to evaluate both training and validation phases. In all cases for all folds; training ACC and validation ACC values converge to the upper limit. Nevertheless, AlexNet has more volatility and has had difficulty converging compared to the proposed architecture. Moreover, the proposed architecture converged before the 200<sup>th</sup> epoch. Training loss values converged to the lower limit. Similarly, the proposed architecture converged to the lower limit before the 200<sup>th</sup> epoch. Due to the

dropout method, some temporary loss increases were observed, but they disappeared towards the last epoch. Similarly, the validation loss values converged to the lower limits. However, only in the proposed architecture, although the 2<sup>nd</sup> fold loss tended to increase, it moved within lower values compared to AlexNet. Also, overfitting or underfitting was not observed in any of the trained models. In the COVID-19 vs No-Findings classification, during the training of AlexNet architecture, average training ACC, training loss, validation ACC, and validation loss were calculated as 98.20%, 0.057, 93.4%, and 0.563, respectively and the proposed model was achieved 100.00%, 0, 96.20%, and 0.269, respectively. Besides, in the Positive vs Negative classification, the proposed model was achieved 99.60%, 0.013, 92.60%, and 0.603, respectively. In order to clearly evaluate the performance of the trained models, the ROC curves for the validation and testing phase of the trained models are given in [Figure 9](#). As can be seen in the figure, the AUC values for mean ROCs were calculated as the lowest 95% and had a deviation of most  $\mp 0.02\%$ . Especially, the ROC curve during the testing phase of the proposed model was almost ideal. Moreover, for this purpose, the best confusion matrices (CM) obtained in the test phase are given in [Figure 10](#). While there were 5 misclassified labels using AlexNet in Experiment 1, 98 of 100 mapping images were correctly classified by the proposed architecture and only one COVID-19 case was misclassified in Experiment 2. Besides, as seen in CM obtained using only 2D ECG spectral images in Experiment 3, the rate of misclassification was high. Further, even though misclassification performance increased in the CM obtained in experiment 4, it misclassified only one COVID-19 case.

#### Comparison with recent studies

Recently, presented studies to automatically diagnose COVID-19 with deep learning have emphasized well-

1 known architecture ResNet [70]. Accordingly, in addition to the experiments performed, generated hexaxial mapping images were trained with ResNet-50 architecture to compare with our proposed architecture. However, overfitting was observed during the training phase of the models. Therefore, sufficient performance could not be achieved during the testing phase of these models (average 70% ACC). The main reason for this was to train the deeper network with an insufficient number of labeled data. Since sufficient performance was not achieved with our input data in architectures that had more layers, the number of layers of the proposed model was not increased further.

14 In this study, we want to draw particular attention to the results of Experiment 4 which reveals that ECG may be a diagnostic tool for COVID-19. In fact, in all conducted statistical analyses of GLCM features, a significant difference was observed between ECGs of COVID-19 and the others; MI, abnormal, and no cardiac findings in spite of having low-resolution images and the restricted number of data. Undoubtedly, we would like to point out that we need more ECG data especially ECGs of mild or asymptomatic COVID-19 patient's to prove our claim. We hope the health science community will share more data on COVID-19.

26 Additionally, many deep learning-based studies have used radiographic images for the detection of COVID-19 and many of them have achieved outstanding classification performance. The following studies can be shown as an example: Al-Waisy et al. [70] achieved accuracy of 99.99%, Dhiman et al. [76] achieved accuracy of 98.54%, Ozturk et al. [14] achieved accuracy of 98.08%, and Ahuja et al. [72] achieved accuracy of 99.4%. The main reason for the success of the mentioned studies is that the most common symptom of COVID-19 disease is lung involvement [77] and the symptoms can be clearly observed on radiographic lung images [78]. Despite this, some studies using CT

and X-ray to diagnose COVID-19 have achieved less accuracy rate than our proposed method. The following studies can be shown as an example: Ismael and Şengür [68] achieved accuracy of 94.7%, Pathak et al. [79] achieved accuracy of 93.02%, Song et al. [67] achieved accuracy of 86%, Amyar et al. [17] achieved accuracy of 94.67%, and Wang et al. [80] achieved accuracy of 82.9%. Moreover, considering the disadvantages of radiological images mentioned in the [Background](#) section, the proposed ECG-based COVID-19 diagnosis method may be more useful than the radiological image-based detection methods. In particular, it can be noted that the ECG is more accessible and harmless than CT or X-ray.

Furthermore, many studies are presented to classify cardiac arrhythmias using multi-lead ECG [42, 81]. Arrhythmias may not be observed in all ECG channels and may be dominant only in some ECG channels. Especially in multi-lead ECG and AI-based classification studies, all channel information should be protected. Otherwise, an abnormal ECG may be misclassified if the prediction is performed through the ECG channel where no abnormality is observed. Since the proposed hexaxial mapping method includes all 12-lead channel information, no channel in which arrhythmias can be observed has been ignored. Moreover, the proposed hexaxial mapping method supports the representation of not only paper-based ECG images but also 2D spectral images of digital ECG signals. Therefore, it can be used in the representation and classification of cardiac arrhythmias from digital ECG signals and can be an alternative to current automated arrhythmia detection approaches.

#### Major contribution of the study

The COVID-19 pandemic has caused many medical challenges. A fast and easily accessible method is required for the early and accurate diagnosis of the disease. Detection of COVID-19 with ECG data using a

1 deep learning approach shows promise as a new diag-  
2 nostic method. In this respect, this paper makes sev-  
3 eral contributions to the literature. These innovative  
4 contributions may be emphasized as follows:

- 5 • A novel, highly sensitive, and harmless method  
6 has been proposed as an alternative to the exist-  
7 ing diagnostic methods to aid in the diagnosis of  
8 COVID-19.
- 9 • A new and effective approach has been proposed  
10 in order to classify paper-based ECG data, where  
11 all ECG-leads can be represented as a single col-  
12 orful 2D image.
- 13 • Differences in the ECG data of patients with  
14 COVID-19 and individuals without any cardiac  
15 findings and patients with various arrhythmias  
16 were demonstrated.
- 17 • The experimental classification results can be ev-  
18 idence for the presence of cardiovascular changes  
19 caused by COVID-19.
- 20 • The advantages of the proposed hexaxial feature  
21 mapping process on classification performance  
22 were demonstrated.
- 23 • A new and simple deep network architecture has  
24 been proposed for 2D image classification and the  
25 deep network hyperparameters were optimized to  
26 yield the best classification performance.

#### 27 Limitations and future scope

28 Nonetheless, some limitations should be noted. In par-  
29 ticular, the hexaxial feature mapping process is very  
30 sensitive to the resolution of paper-based ECG images.  
31 Resolution variations in ECG images may cause dif-  
32 ferentiation in the features obtained through GLCM  
33 and may affect the color intensity of hexaxial maps.  
34 Further, while performing the segmentation of ECG-  
35 lead images, the size of the selected rectangular frame  
36 must be kept constant. It should be noted that the  
37 segmentation process can be standardized by using a  
38 smart-phone application that guides the user for tak-

ing the right ECG image from the paper-based ECG  
report. Additionally, although the proposed method  
is designed as a patient-independent approach and its  
robustness has been tested with various experimen-  
tal scenarios, it needs to be evaluated with different  
datasets. The main limitation here is the lack of access  
to the COVID-19 patients' ECG data and the lack of  
a sufficient amount of data. Moreover, the dataset in  
which the proposed method is tested does not contain  
any information about the severity of the condition  
of COVID-19 patients. This prevents an evaluation  
of the occurrence of COVID-19-induced cardiovascu-  
lar changes.

Another limitation is that there may be variability  
in the number of leads and derivation when collecting  
ECG data. Although the proposed method requires 12  
basic leads, ECG data collected from various deriva-  
tions can be adapted to the hexaxial mapping process.  
It should also be noted that this work aims to dis-  
cuss the ability to automatically distinguish COVID-  
19 ECG data from other types of ECG data. Although  
recent studies [30, 32–34, 51] have reported various  
cardiovascular changes in most of the patients, they  
also reported infected patients without any cardiovas-  
cular changes. Therefore, the sensitivity of the pro-  
posed method is related to the observability of cardio-  
vascular changes. Furthermore, there are concerns that  
COVID-19 may not be the main source of cardiovas-  
cular changes in ECG data [25]. Thus, two main issues  
could be addressed in future research; further research  
should be attempted to specify COVID-19-induced  
cardiovascular changes, and the current method should  
be tested on a more robust dataset.

#### 72 Conclusion

73 In this study, a novel and effective approach is pro-  
74 posed to automatically detect COVID-19 using paper-  
75 based ECG report images. This study aims to distin-  
76 guish the ECGs of COVID-19 patients from various

1 types of ECGs. Accordingly, a novel method based on  
 2 representing 12-lead paper-based ECG images as 2D  
 3 colorful images has been proposed and the generated  
 4 colored images are then fed into a new CNN architec-  
 5 ture to detect COVID-19. While recent state-of-the-art  
 6 studies have revealed that COVID-19 can lead to car-  
 7 diovascular complications directly or indirectly, ECG  
 8 data is used for the first time to automatically diagnose  
 9 COVID-19, to the best of our knowledge.

10 Various experiments are conducted to evaluate the  
 11 robustness of the proposed approach and compare its  
 12 performance. The results demonstrated that the pro-  
 13 posed method achieved promising performance in the  
 14 diagnosis of COVID-19 using ECG data. Furthermore,  
 15 the proposed deep network significantly improved clas-  
 16 sification accuracy compared to well-known architec-  
 17 tures and the proposed hexaxial mapping procedure  
 18 not only decreased computational cost, but it also  
 19 significantly increased classification performance. Fur-  
 20 thermore, the capability of the proposed approach  
 21 to differentiate COVID-19 ECGs can be the proof  
 22 of the presence of COVID-19-induced cardiovascular  
 23 changes.

24 In the light of all findings, we can say that; the pro-  
 25 posed approach can potentially be used as a faster,  
 26 more harmless, more accessible, cost-effective, and  
 27 more sensitive automatically diagnostic method to de-  
 28 tect COVID-19 than the current methods. In future  
 29 works, the presented ECG-based COVID-19 diagno-  
 30 sis method can be simply adapted to real-time cloud-  
 31 based systems and can be easily performed on mo-  
 32 bile device-based decision-making applications. Thus,  
 33 it may help healthcare professionals by providing a fast  
 34 and effective solution to diagnose COVID-19, it may  
 35 reduce both the contamination and the hospital bur-  
 36 den by preventing unnecessary hospital visits.

## Abbreviations

ACC: Accuracy; AF: Atrial Fibrillation; AI: Artificial Intelligence; ANOVA:  
 Analysis of Variance; CM: Confusion Matrices; CNN: Convolutional Neural  
 Network; Conv: Convolution; COVID-19: Coronavirus Disease 2019; CT:  
 Computed Tomography; CWT: Continuous Wavelet Transform; ECG:  
 Electrocardiogram; F1-S: F1-Score; FNR: False-negative Rate; FPR:  
 False-positive Rate; GLCM: Gray-Level Co-Occurrence Matrix;  
 ILSVRC2012: Large Scale Visual Recognition Challenge in 2012; IoT:  
 Internet of Things; MI: Myocardial Infarction; MSE: Mean Squared Error;  
 PRE: Precision; RBBB: Right Bundle Branch Block; REC: Recall; ReLU:  
 Rectified Linear Units; ROC-AUC: Area Under the Receiver Operating  
 Characteristic Curve; rRT-PCR: Real-time Reverse  
 Transcriptase-polymerase Chain Reaction; RVPO: Right Ventricular  
 Pressure Overload; SARS-CoV-2: Severe Acute Respiratory Syndrome  
 Coronavirus 2; SPE: Specificity; STFT: Short-time Fourier Transform;  
 SVM: Support Vector Machines; WHO: World Health Organization.

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## Authors' contributions

MAO: Conceptualization of this study, Methodology, Software, Validation,  
 Formal analysis, Investigation, Data curation, Writing-Original draft,  
 Writing-Review and editing, Visualization. GDO: Investigation,  
 Writing-Original draft, Writing-Review and editing, Visualization. OG:  
 Conceptualization of this study, Formal analysis, Investigation,  
 Writing-Original draft, Writing-Review and editing. All authors provided  
 input into drafts and approved the final draft of the manuscript.

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## Availability of data and materials

Python and MATLAB source codes, and segmented and preprocessed  
 dataset are available from:

<https://github.com/mkfzdmr/COVID-19-ECG-Classification>

The dataset used in this work is publicly available at:

<http://dx.doi.org/10.17632/gwbz3fsgp8.1>

## Ethics approval and consent to participate

The authors declare that the work described has been carried out in  
 accordance with the Declaration of Helsinki of the World Medical  
 Association revised in 2013 for experiments involving humans. The research  
 related to human use complies with all the relevant national regulations  
 and institutional policies. Human ECG data were obtained from [52] which  
 compiles all relevant ethical processes as indicated in the paper.

## Consent for publication

The authors declare that this report does not contain any personal  
 information that could lead to the identification of the patient(s).

## 1 Competing interests

2 The authors declare that they have no known competing financial or  
3 personal relationships that could be viewed as influencing the work reported  
4 in this paper.

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**Figure 1 Representation of the proposed framework**, includes five-step: (i) ECG image dataset acquisition, (ii) segmentation, pre-image-processing, and image enhancement, (iii) application of GLCM and extractions of some of their properties (includes statistical analysis), (iv) ECG hexaxial feature mapping process, and (v) designing, training, validating, and testing the proposed deep network (\*GLCM: Gray Level Co-occurrence Matrix, paper-based ECG report number: 211 with the label: COVID-19).

**Figure 2 Examples of background removal processes:** (a) segmented paper-based ECG image, (b) paper-based ECG image without background lines, (c) binarized paper-based ECG image, and (d) eventual paper-based ECG image.

**Figure 3 One-way ANOVA results within a box plot for each related GLCM features.** All normalized GLCM features obtained from binary ECG images were verified to be statistically significant relative to each other ( $p < 0.0001$  for all binary groups). Each group has a total of 4500 samples: 18-lead  $\times$  250 paper-based ECG reports (C: COVID-19, N: No-Findings).

**Figure 4 ECG electrode location representations:** (a) 3D representation of hexaxial and horizontal reference systems of 12-lead ECG acquisition, (b) 2D mapping of 3D hexaxial (limb leads) and horizontal (precordial leads) reference systems on the coronal plane; and an example of hexaxial feature mapping by using GLCM energies for (c) No-Finding class (Report Number: 182) and (d) COVID-19 class (Report Number: 16).

**Figure 5 Graphical representation of proposed architecture** (Conv: Convolution, FC: Fully Connected, ReLU:Rectified Linear Unit).

**Figure 6 Graphical representation of modified stratified k-fold cross-validation.** The number of folds (k) was chosen as 5 in this study. In each fold, the training size, validation size, and test size are 400, 100, and 100, respectively.

**Figure 7 One-way ANOVA results for Negative and Positive comparison** within a box plot using COVID-19 GLCM energies and GLCM energies of other ECG groups. Normalized COVID-19 GLCM energies obtained from binary ECG images were verified to be statistically significant to each ECG group ( $p < 0.0001$  for all cases). Each group has a total of 1494 samples: 18-lead  $\times$  83 paper-based ECG reports.

**Figure 8** Graphs of training ACC (a, b, c), training Loss (d, e, f), validation ACC (g, h, i), and validation Loss (j, k, l) per Epoch during the training and validation phases. The **left column** indicates trained with Alexnet for COVID-19 vs No-Findings classification, the **mid column** indicates trained with modified Alexnet for COVID-19 vs No-Findings classification, and the **right column** indicates trained with modified Alexnet for Negative vs Positive classification.

**Figure 9 The ROC curves** of COVID-19 vs No-Findings classification using AlexNet during (a) validation phase and (b) testing phase, using proposed architecture during (c) validation phase and (d) testing phase, and the ROC curves of Positive vs Negative classification using proposed architecture during (e) validation phase and (f) testing phase.

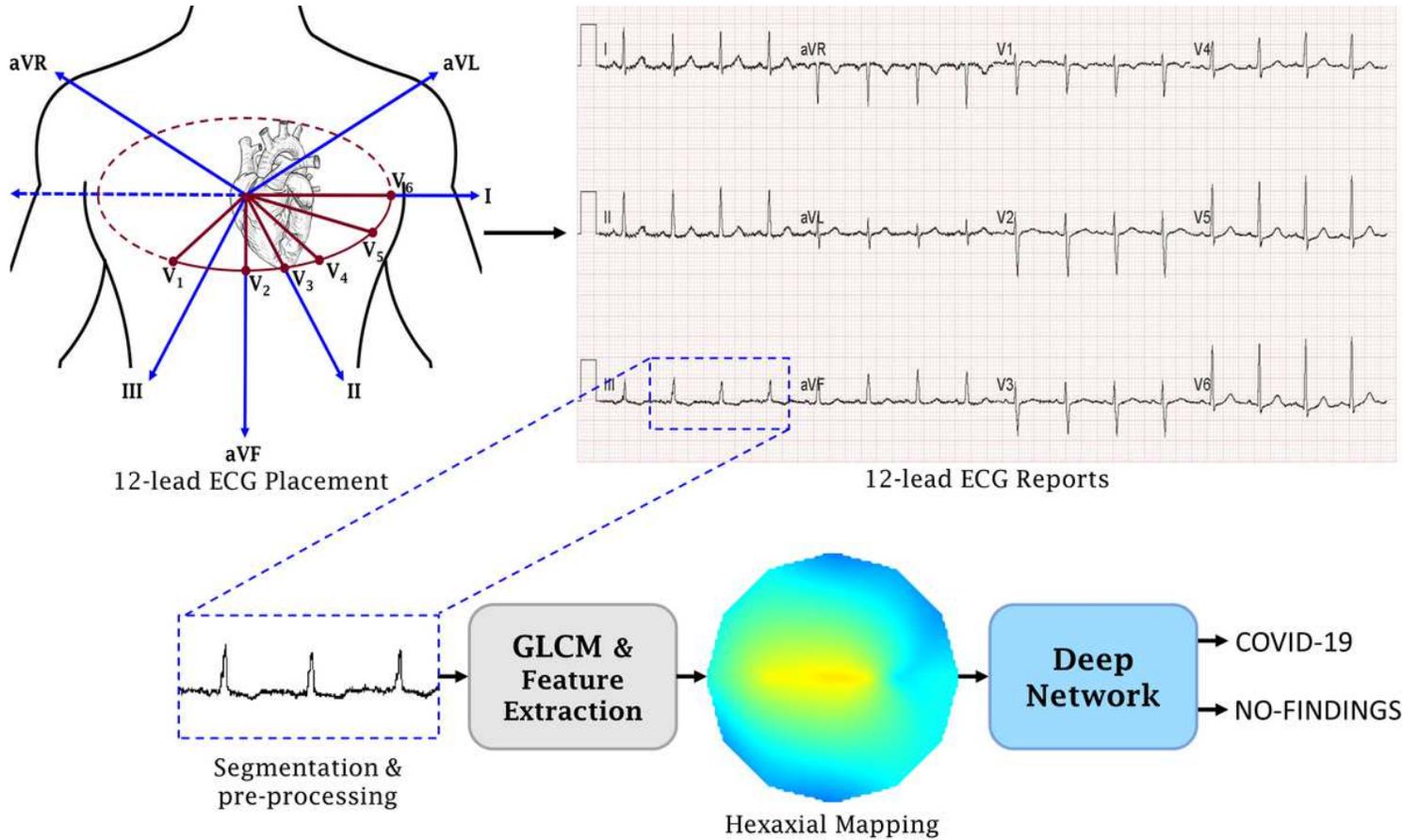
**Figure 10 The best confusion matrices** obtained during the testing phases: (a) fold-5 in Experiment 1 (COVID-19 vs No-Findings), (b) fold-4 in Experiment 2 (COVID-19 vs No-Findings), (c) fold-1 in Experiment 3 (COVID-19 vs No-Findings), and (d) fold-5 in Experiment 4 (Positive vs Negative).

**Table 1** Performance evaluation results of trained models.

		Performance Evaluation Metrics									
		Folds	ACC	PRE	REC	SPE	F1-S	AUC	Loss	MSE	TT
<b>Experiment 1</b> <b>COVID-19 vs No-Findings</b> via AlexNet	Fold-1	91.00	88.68	94.00	88.00	91.26	97.92	0.283	0.090	103.91	
	Fold-2	<b>95.00</b>	92.45	98.00	92.00	95.15	96.44	0.680	0.050	101.50	
	Fold-3	93.00	89.09	98.00	88.00	93.33	97.16	0.451	0.070	101.56	
	Fold-4	94.00	94.00	94.00	94.00	94.00	97.30	0.533	0.060	101.47	
	Fold-5	<b>95.00</b>	94.12	96.00	94.00	95.05	98.60	0.317	0.050	101.44	
	<b>Average</b>	<b>93.60</b>	<b>91.67</b>	<b>96.00</b>	<b>91.20</b>	<b>93.76</b>	<b>97.48</b>	<b>0.453</b>	<b>0.064</b>	<b>101.98</b>	
<b>Experiment 2</b> <b>COVID-19 vs No-Findings</b> via Proposed Architecture	Fold-1	94.00	90.74	98.00	90.00	94.23	97.36	0.721	0.060	105.10	
	Fold-2	96.00	92.59	100.0	92.00	96.15	99.60	0.203	0.040	103.41	
	Fold-3	97.00	96.08	98.00	96.00	97.03	99.84	0.151	0.030	102.83	
	Fold-4	<b>98.00</b>	98.00	98.00	98.00	98.00	99.88	0.086	0.020	102.86	
	Fold-5	96.00	94.23	98.00	94.00	96.08	99.08	0.300	0.040	101.87	
	<b>Average</b>	<b>96.20</b>	<b>94.33</b>	<b>98.40</b>	<b>94.00</b>	<b>96.30</b>	<b>99.15</b>	<b>0.292</b>	<b>0.038</b>	<b>103.21</b>	
<b>Experiment 3</b> <b>COVID-19 vs No-Findings</b> using only 2D ECG Spectral Images	Fold-1	<b>84.83</b>	82.62	88.22	81.44	85.30	93.56	0.348	0.152	532.43	
	Fold-2	81.50	78.46	85.68	77.50	81.91	91.65	0.650	0.177	526.35	
	Fold-3	81.85	79.08	84.82	77.77	81.85	91.98	0.592	0.173	525.54	
	Fold-4	80.17	80.12	82.26	77.89	81.18	87.16	0.785	0.237	528.07	
	Fold-5	77.06	76.80	79.53	74.43	78.14	84.75	0.845	0.362	529.78	
	<b>Average</b>	<b>81.08</b>	<b>79.42</b>	<b>84.10</b>	<b>77.81</b>	<b>81.68</b>	<b>89.82</b>	<b>0.644</b>	<b>0.220</b>	<b>528.43</b>	
<b>Experiment 4</b> <b>Negative vs Positive</b> via Proposed Architecture	Fold-1	92.00	88.89	96.00	88.00	92.31	94.08	0.831	0.080	106.95	
	Fold-2	<b>95.00</b>	92.45	98.00	92.00	95.15	98.04	0.297	0.050	103.28	
	Fold-3	91.00	88.68	94.00	88.00	91.26	95.00	0.520	0.090	103.43	
	Fold-4	94.00	90.74	98.00	90.00	94.23	94.06	0.663	0.060	103.71	
	Fold-5	93.00	92.16	94.00	92.00	93.07	93.70	0.827	0.070	102.23	
	<b>Average</b>	<b>93.00</b>	<b>90.58</b>	<b>96.00</b>	<b>90.00</b>	<b>93.20</b>	<b>94.98</b>	<b>0.628</b>	<b>0.070</b>	<b>103.92</b>	

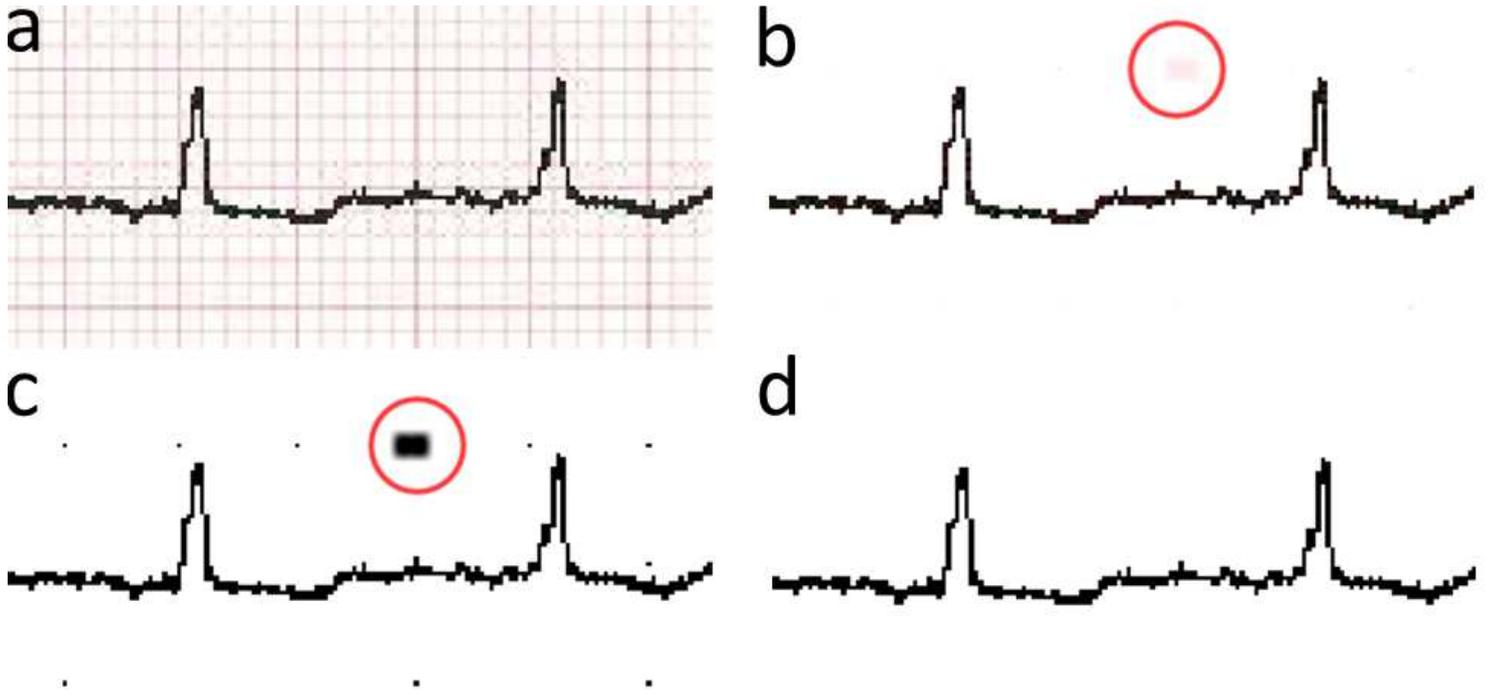
\* Loss: Cross-Entropy Loss, TT: Training Time (sec), and all ACC, PRE, REC, SPE, F1-S, and ROC-AUC values are given as %.

# Figures



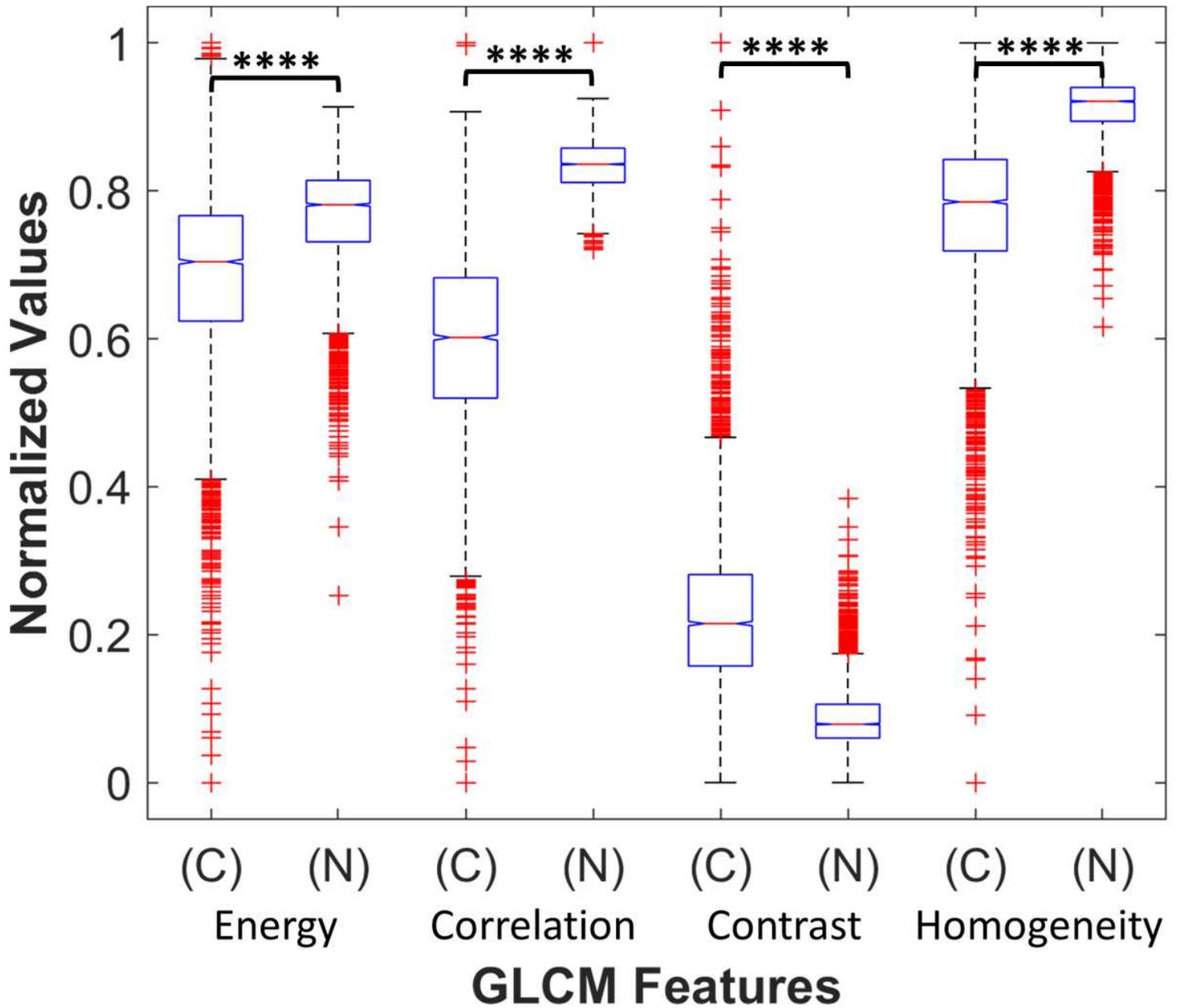
**Figure 1**

Representation of the proposed framework, includes ve-step: (i) ECG image dataset acquisition, (ii) segmentation, pre-image-processing, and image enhancement, (iii) application of GLCM and extractions of some of their properties (includes statistical analysis), (iv) ECG hexaxial feature mapping process, and (v) designing, training, validating, and testing the proposed deep network (\*GLCM: Gray Level Co-occurrence Matrix, paper-based ECG report number: 211 with the label: COVID-19).



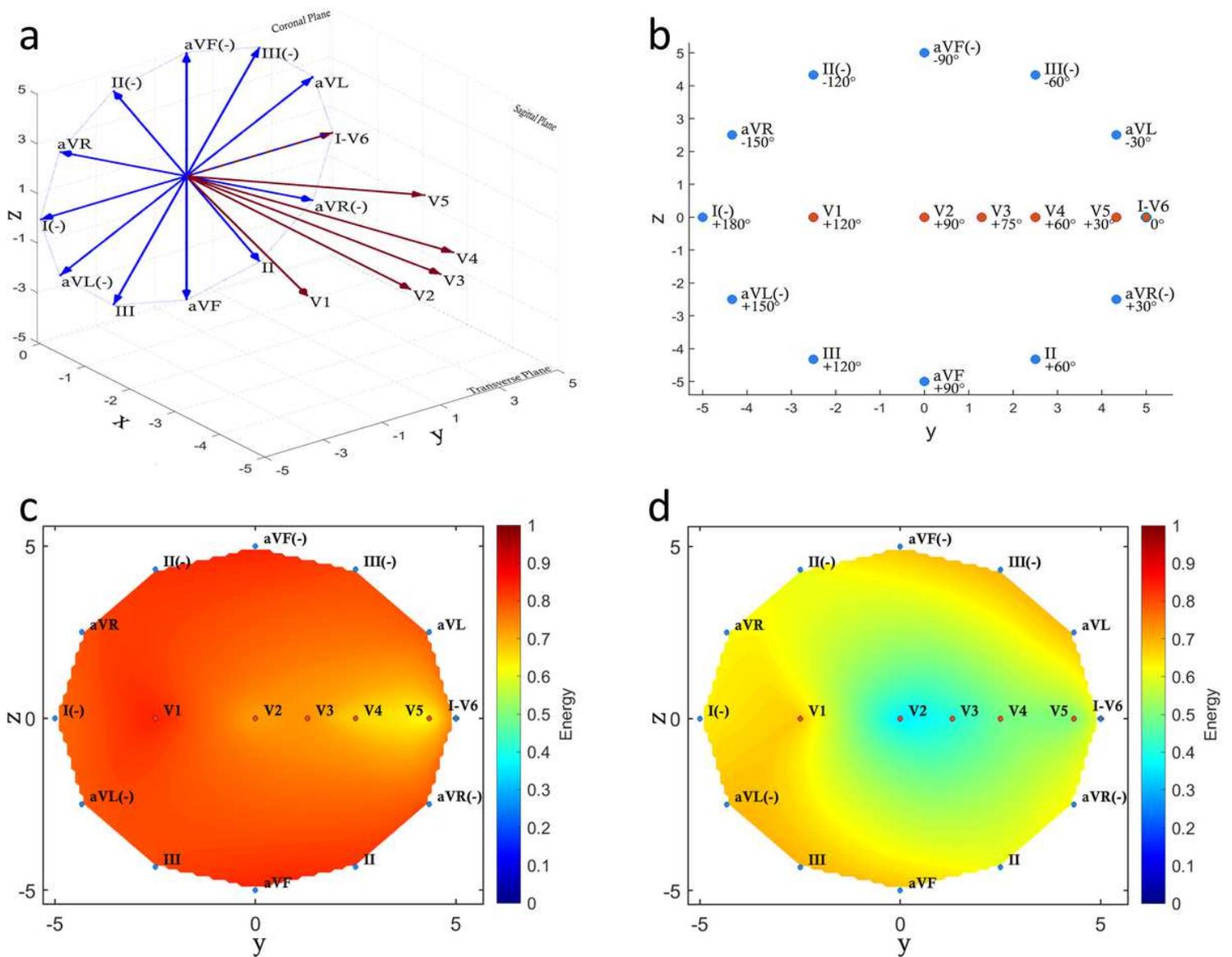
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Examples of background removal processes: (a) segmented paper-based ECG image, (b) paper-based ECG image without background lines, (c) binarized paper-based ECG image, and (d) eventual paper-based ECG image.



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One-way ANOVA results within a box plot for each related GLCM features. All normalized GLCM features obtained from binary ECG images were verified to be statistically significant relative to each other ( $p < 0.0001$  for all binary groups). Each group has a total of 4500 samples: 18-lead x 250 paper-based ECG reports (C: COVID-19, N: No-Findings).



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ECG electrode location representations: (a) 3D representation of hexaxial and horizontal reference systems of 12-lead ECG acquisition, (b) 2D mapping of 3D hexaxial (limb leads) and horizontal (precordial leads) reference systems on the coronal plane; and an example of hexaxial feature mapping by using GLCM energies for (c) No-Finding class (Report Number: 182) and (d) COVID-19 class (Report Number: 16).

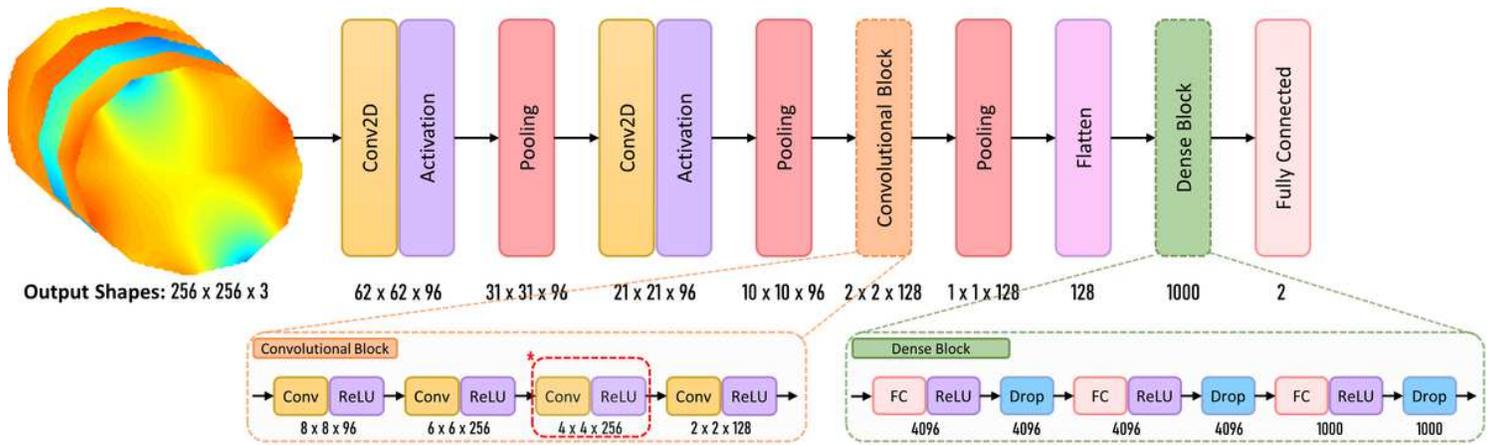


Figure 5

Graphical representation of proposed architecture (Conv: Convolution, FC: Fully Connected, ReLU: Rectified Linear Unit).

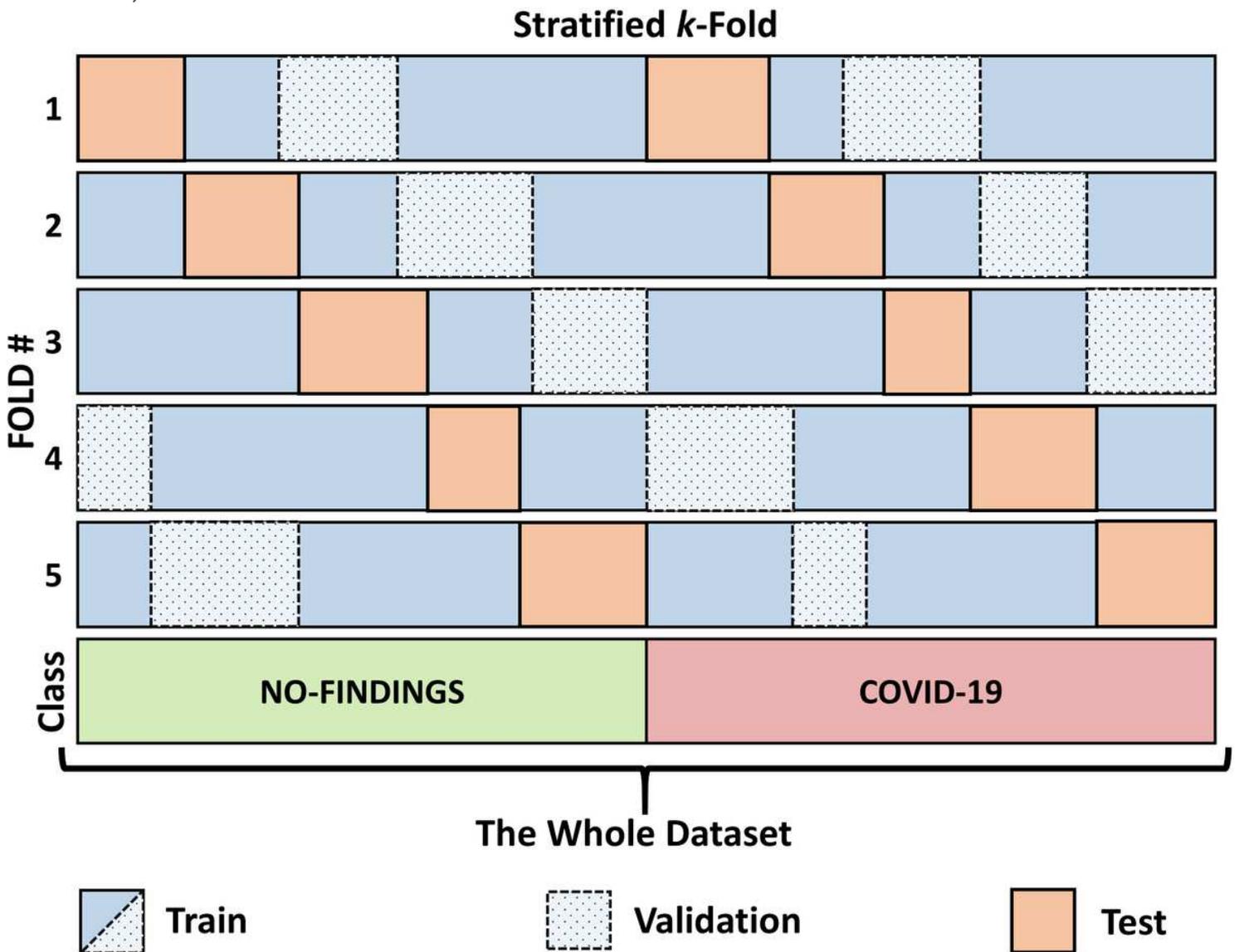


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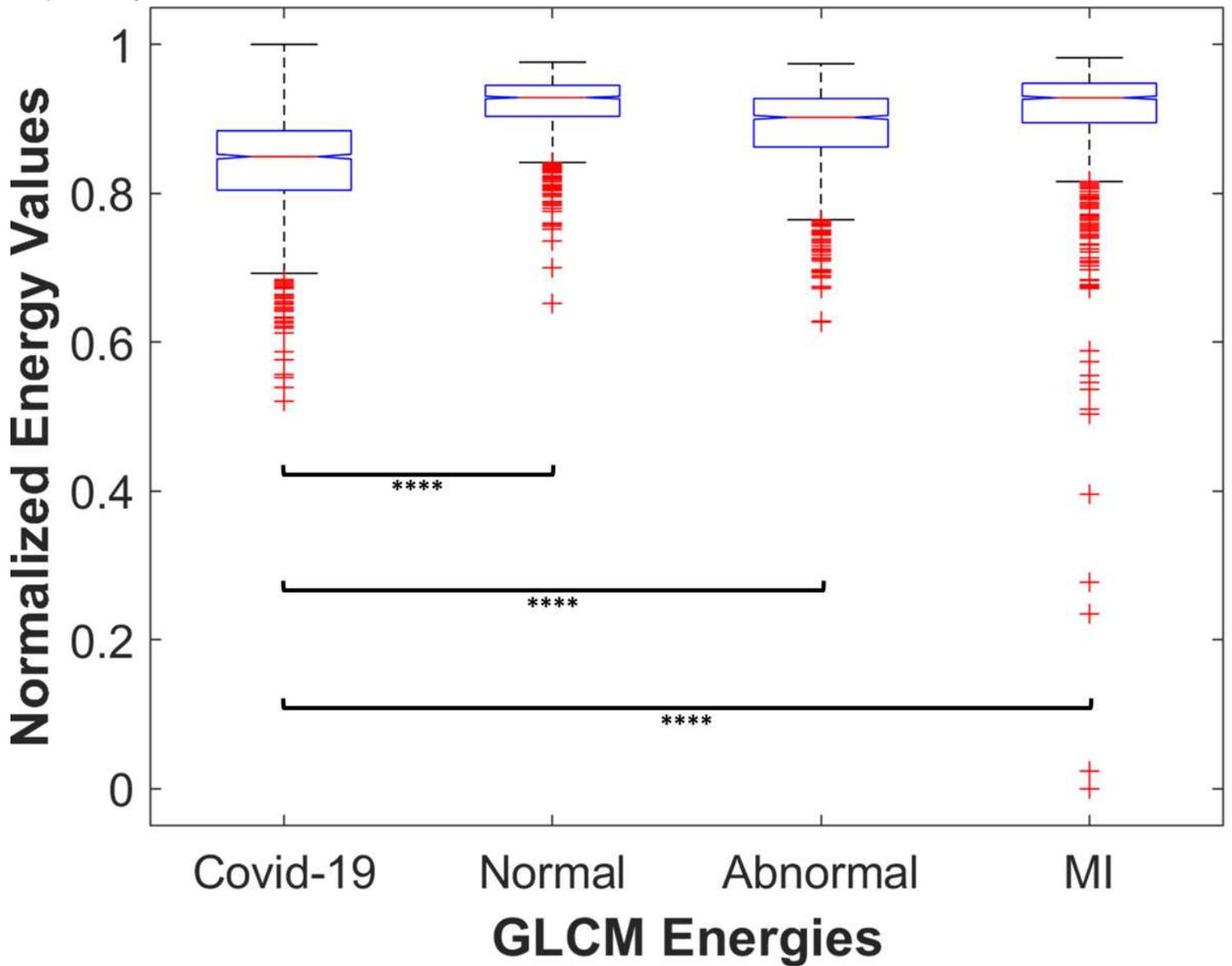
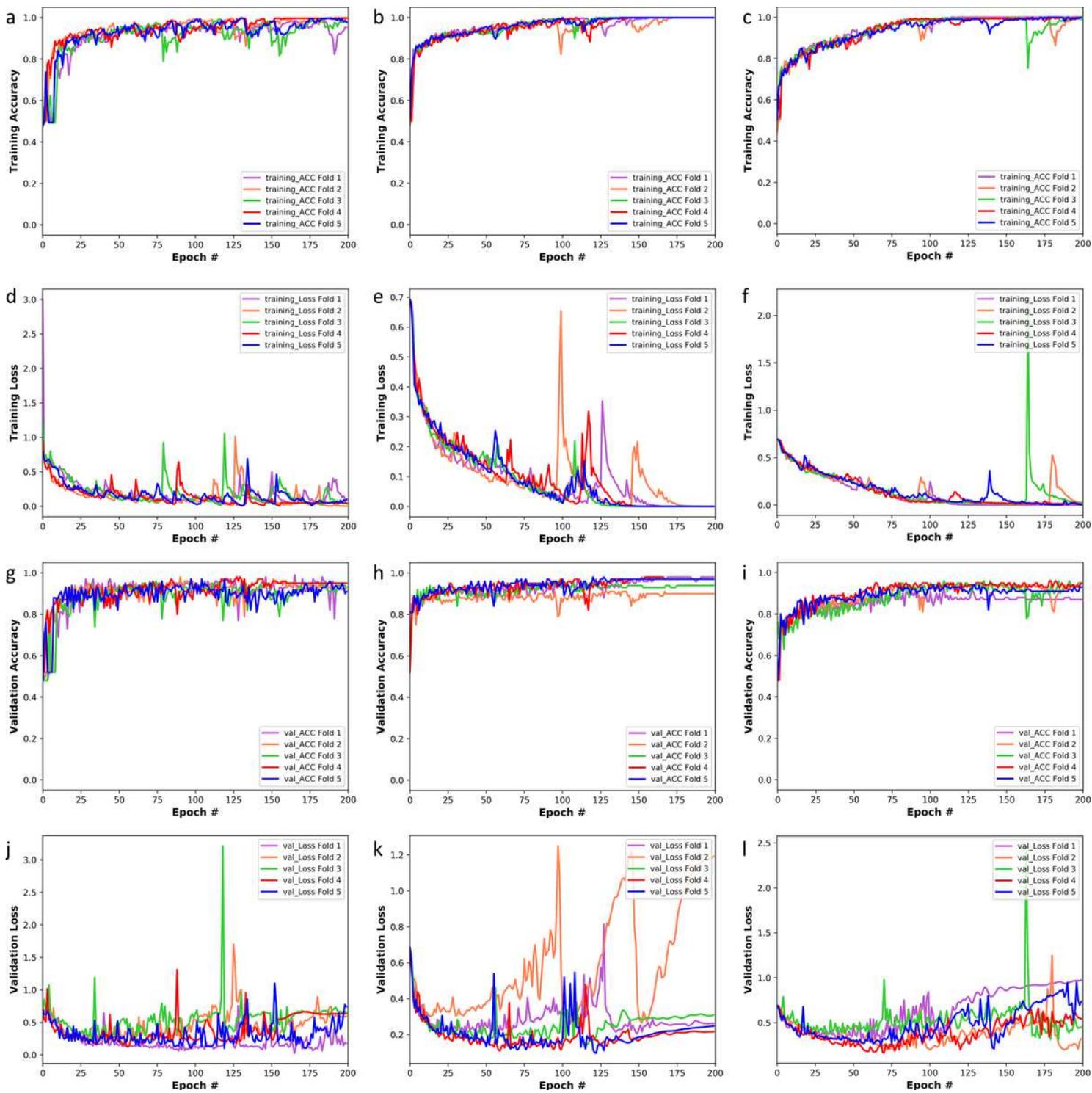


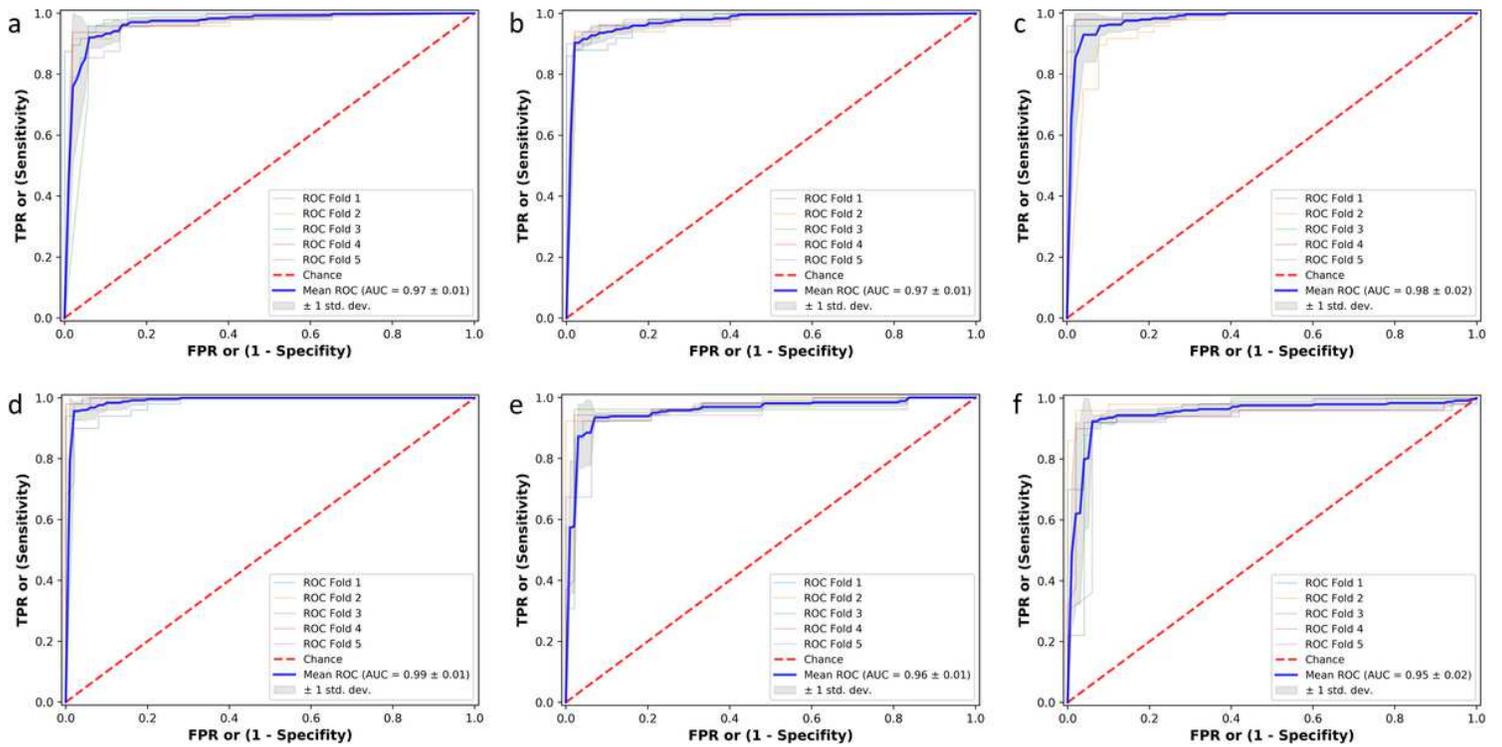
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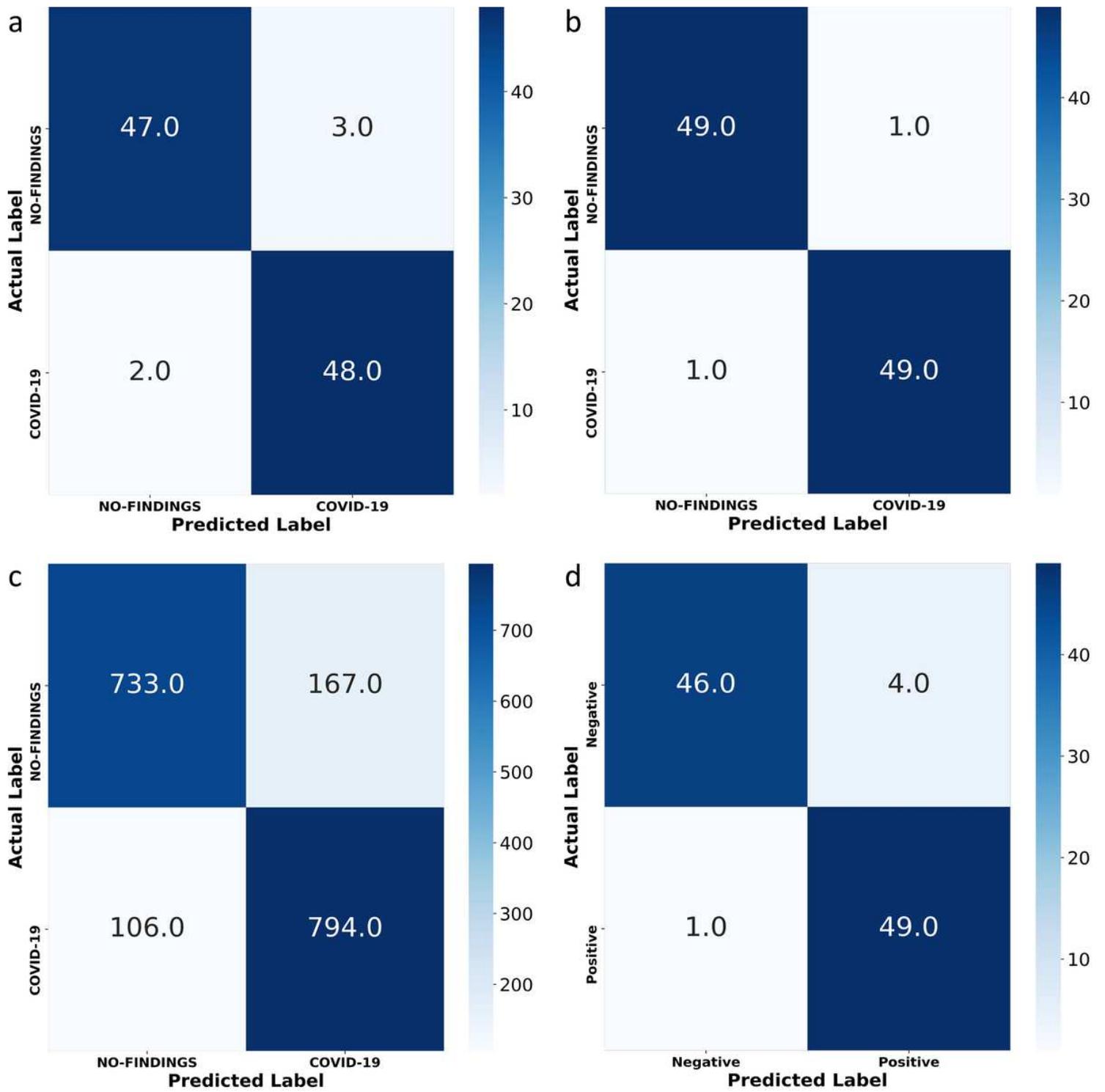


Figure 10

The best confusion matrices obtained during the testing phases: (a) fold-5 in Experiment 1 (COVID-19 vs No-Findings), (b) fold-4 in Experiment 2 (COVID-19 vs No-Findings), (c) fold-1 in Experiment 3 (COVID-19 vs No-Findings), and (d) fold-5 in Experiment 4 (Positive vs Negative).