Research Article

ResNet-50 for 12-Lead Electrocardiogram Automated Diagnosis

Nizar Sakli,1,2 Haifa Ghabri,2 Ben Othman Soufiene,3 Faris. A. Almalki,4 Hedi Sakli,1,2 Obaid Ali,5 and Mustapha Najjari6

1EITA Consulting, 5 Rue du Chant des Oiseaux, Montesson 78360, France
2MACS Research Laboratory RL16ES22, National Engineering School of Gabes, Gabes University, Gabes 6029, Tunisia
3PRINCE Laboratory Research, ISITcom, Hammam Sousse, University of Sousse, Sousse 4023, Tunisia
4Department of Computer Engineering, College of Computers and Information Technology, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia
5Ibb University, Department of Computer Science and Information Technology, Ibb, Yemen
6LR18ES34 PEESE, National Engineering School of Gabes, Gabes University, Gabes 6029, Tunisia

Correspondence should be addressed to Obaid Ali; obaid.ali2016@gmail.com

Received 2 November 2021; Revised 13 January 2022; Accepted 22 March 2022; Published 28 April 2022

Academic Editor: Yassine Maleh

Copyright © 2022 Nizar Sakli et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Nowadays, the implementation of Artificial Intelligence (AI) in medical diagnosis has attracted major attention within both the academic literature and industrial sector. AI would include deep learning (DL) models, where these models have been achieving a spectacular performance in healthcare applications. According to the World Health Organization (WHO), in 2020 there were around 25.6 million people who died from cardiovascular diseases (CVD). Thus, this paper aims to shed the light on cardiology since it is widely considered as one of the most important in medicine field. The paper develops an efficient DL model for automatic diagnosis of 12-lead electrocardiogram (ECG) signals with 27 classes, including 26 types of CVD and a normal sinus rhythm. The proposed model consists of Residual Neural Network (ResNet-50). An experimental work has been conducted using combined public databases from the USA, China, and Germany as a proof-of-concept. Simulation results of the proposed model have achieved an accuracy of 97.63% and a precision of 89.67%. The achieved results are validated against the actual values in the recent literature.

1. Introduction

Nowadays, the medical field requires new techniques and technologies in order to evaluate information objectively. According to data from the World Health Organization (WHO), cardiovascular diseases (CVD) represent the leading cause of death globally, where the CVDs account for more than 30% of global mortality each year, and it is estimated to reach around 130 million people by 2035 [1]. Therefore, researchers are developing new methods for preventing, detecting, and treatment of diseases related to the CVD. There are many types of cardiovascular abnormalities, while this study focuses on 26 anomalies, which will be cited later.

The electrocardiogram (ECG) is a recording of the electrical activity of the human heart, which is deemed as a noninvasiveness and real-time exam. It is still one of the essential pillars of the diagnosis of cardiac problems. In recent years, the methods of analysing CVDs have been strengthened by the introduction of imaging procedures, especially the echocardiogram. However, this does not change the importance and usefulness of ECGs, and the parameters could be extracted from this signal. The number of leads on a typical ECG acquisition equipment divides it into 1-lead, 3-lead, 6-lead, and 12-lead ECG. The 12-lead ECG is the most often utilized kind in clinical practice due to its ability to concurrently capture the potential changes of 12 sets of electrode patches attached to the body in standardized places [2]. When comparing to other types of ECG acquisition equipment, 12-lead ECG provides more information on cardiac activity and is frequently utilized in hospital for diagnosis and treatment. In fact, many essential parameters...
can be extracted from the ECG signal; for instance, the duration and patterns of the various waves, which are indicative of specific cardiac abnormalities.

Professional doctors frequently make ECG analysis and interpretation [3], which is heavily reliant on training, qualifications, experiences, and expertise; thus it is difficult to extract all information from ECG signals [4, 5]. In practice, manual detection of characteristic waves of the ECG signal and classification of heartbeats are difficult and tedious tasks, especially to analyse long-term recordings as Holter examination or ambulatory cases for continuous monitoring in intensive care and resuscitation wards.

With the progress of physical hardware technologies and algorithm, computer-assisted medical diagnoses (CAMD) have become vital in diagnosing CVDs. CAMD based on ECG signals can give professional suggestions or decide instantly by searching for characteristic patterns. It can help doctors make diagnoses and appears to be required due to the huge number of patients in critical care units where they need continuous monitoring. This is how CAMD looked to use the ECG signal to help in cardiac diagnosis. These systems should be easy to set up, upgradeable, accurate, durable, and dependable. The authors of [6] emphasised the importance of using optimization techniques to enhance efficiency for prediction in healthcare applications.

Over the past decades, many techniques for detecting CVDs have been proposed, where some of them are based on signal processing techniques and classification algorithms like support vector machines (SVMs). Deep neural network-based machine learning (ML) and convolutional neural networks (CNN) methods have lately emerged as efficient tools in large applications such as computer vision and natural language processing. Noticeably, coupling ML and DL with healthcare has brought up massive advantages and researchers are striving to find more innovative solutions.

This work aims to classify 27 classes, with ECG signals containing 26 types of CVDs and normal sinus rhythm. This classification where we used four databases contains 42511 ECG records to train, validate, and evaluate models such as CPSC 2018, CPSC 2018-Extra [7], PTB-XL [8], and Georgia [7]. The used dataset contains ECG 12-leads signals, which is a typical ECG set used in clinical cases and hospitals. It is trained with a model based on Residual Neural Networks-50 (ResNet-50) from CNN methods, which is known as one of the most efficient models in classification.

The rest of this paper is structured as follows. Section 2 presents an overview of related works in the literature; Section 3 represents background information on the interpretation of an ECG. Section 4 describes the proposed model and our simulation workflow. The proposed ECG classification model results are discussed in Section 5. Finally, Section 6 presents the conclusion and future works.

2. Related Work

DL is a subdivision of ML; ML is a subdivision of AI and AI is enabling the machine to act like a human. ML is a way for achieving AI using algorithms trained on data, while DL is inspired by the structure of the human brain or also known as an artificial neural network. The features in ML are picked out with an expert in the domain, whereas in DL they are detected by the neural network without human intervention. That is why DL needs much higher volume of data to be trained to obtain best performance. AI has been shown in numerous experiments to be capable of automatically identifying anomalies registered by an ECG.

Generally, the databases used in papers about ECG diagnosis are public. The first one is from PhysioNet, Massachusetts Institute of Technology-Beth Israel Hospital (MITBIH) [9] which contained only 49 recordings with 30-minute length of each subject, including five classes, normal (N), ventricular ectopic (V), supraventricular ectopic (S), fusion (F), and unknown (Q). Enabio et al. [10] used MITBIH as a database for ECG classification [11–16]. The second database largely used is Physiological Signal Challenge 2018 (CPSC) [7] which is a public too. It comprises 687,712 lead ECG recordings including eight arrhythmias IAVB (1st degree AV block), AF (atrial fibrillation), LBBB (left bundle branch block), PAC (premature atrial contraction), RBBB (complete right bundle branch block), and SNR (sinus normal rhyme) [17–19]. The third one is Physikalisch Technische Bundesanstalt (PTB) [20] diagnostic database, which contains 54,912 lead ECG records from 290 individuals [21–23]. Selvalingam et al. [24] used private databases to predict ventricular arrhythmias with a DL model, CNN. In addition, Smith et al. [25] collected their data to interpret ECG arrhythmias.

Some studies instead have used more than one. For example, Li et al. [26] used five databases (FANTASIA, CEBSDB, NSRDB, STDB, and AFID). However, they do not combine the data to categorize ECG; instead, they test their model for each data set separately. Zhang et al. [27] used four databases, Acharya et al. [28] constructed 4 sets from a combination of three databases (MITBIH [9], FANTASIA [29], and BIDMC [30]). The study varied on using balanced and imbalanced ones. Wang et al. [31] used two databases (MIT-BIH [9], CPSC2018 [7]) to classify ECG with a recurrent neural network (RNN) model. Table 1 lists the different databases used in classifying the ECG signals.

In fact, in their workflows, ML methods consider four fundamental steps:

(i) Signal preprocessing, which includes resampling, noise removal (e.g., band-pass filters), and signal normalization/standardization.

(ii) Heartbeat segmentation, which entails detecting the R-peak (e.g., QRS complex) using algorithms like Pan and Tompkins algorithm [32], the open-source GQRS software supplied by the PhysioNet community.

(iii) Feature extraction, which entails converting raw signals into features that are most suited to the job at hand (e.g., classification, prediction, and regression.).

(iv) ECG signal analysis using traditional machine learning approaches such as multilayer perceptron (MLP) and decision trees.
3. Background Knowledge

It is critical to comprehend electrical cardiac function, since the heart is a mechanical organ that ensures periodic contraction and relaxation. Cells grouped at the nodal level are responsible for an electrical flow that spreads to nearby heart cells (myocardial). Following that, it recontacts to be able to expel blood from other organs.

3.1. ECG Principal. The ECG is a recording of the electrical activity of the heart, which is usually shown as a graph of voltage values vs. time. Electrodes are used to detect electrical changes caused by cardiac muscle cell depolarization and repolarization at a distance from the heart, through the skin. To note, an electrocardiograph is used in this examination. Figure 1 represents a simplified diagram of the conductive elements of the heart, which consists of conductive tissues which are the bundle of His, Bachmann’s bundle, the left and right bundle branches, the Purkinje fibres, and cardiac myocytes themselves. Contractile tissues are the atrial and ventricular wall myocytes. This figure is vital in showing the main components of the heart, so extracting data and signals can be done in more accurate way.

3.2. The Foundation of ECG Interpretation. ECG interpretation includes an assessment of the morphology (appearance) of the waves and intervals on the ECG curve. Therefore, ECG interpretation requires a structured assessment of the waves and intervals. Figure 2 shows a depolarization/repolarization phase of the heart that are represented electrocardiographically by various P waves, QRS, and T waves.

(i) P wave: This is a result of atrial depolarization, which is initiated by the sinus node. Pacemaker cells at this node carry the signal to the right and left atria. The ECG demonstrates abnormal atrial repolarization.

(ii) QRS complex: This is the average of the inner (endocardial) and outer (epicardial) cardiomyocyte depolarization waves. A typical QRS pattern is formed when endocardial cardiomyocytes depolarize somewhat earlier than the outer layers.

(a) The Q wave is the first negative deflection following the P wave. The Q is missing if the first deflection is not negative.

(b) The R wave is the positive deflection.

(c) The S wave is the negative deflection that occurs following the R wave.

(iii) T wave: It indicates the ventricular repolarization. During the T wave, there is no action in the heart muscle.

| Database     | Subjects | Records | Duration | Frequency (Hz) | Leads | References       |
|--------------|----------|---------|----------|----------------|-------|-----------------|
| MITBIH [9]   | 47       | 48      | 30 min   | 360            | 2     | [10–13]         |
| CPSC 2018 [7]| 6877     | 6877    | 6–60 sec | 500            | 12    | [14–16]         |
| PTB [19]     | 290      | 549     | Not specified | 1000       | 12    | [18–20]         |
| Fantasia [29]| 40       | 40      | 120 min  | 250            | Not specified | [23–25]     |
| BIDMC [30]   | Not specified | 53   | 8 min    | 125            | 2     | [26]            |

Table 1: Overview of various databases using ECG classification.
Pathologies or abnormalities in ECG analysis are discovered and categorized based on their departure from normal cardiac rhythm. Normal sinus rhythm (NSR) refers to normal cardiac activity in which there is no deviation or change in the morphology of the ECG signal.

This paper focuses on classifying 27 classes of ECG signal; the classes are 1st Degree AV Block (IAVB), Low QRS Voltages (LQRSV), Right Axis Deviation (RAD), Atrial Fibrillation (AF), Nonspecific Intraventricular Conduction (NSIVCB), Atrial Flutter (AFL), Bradycardia (Brady), Complete Right Bundle, Branch Block (CRBBB), Incomplete Right Bundle Branch Block (IRBBB), Left Anterior Fascicular Block (LAnfb), Pacing Rhythm (PR), Right Bundle Branch Block (RBBB), Premature Atrial Contraction (PAC), Premature Ventricular Contractions (PVC), Sinus Arrhythmia (SA), Sinus Bradycardia (SNR), Sinus Tachycardia (Stach), Superior ventricular Premature Beats (SVPB), Left Axis Deviation (LAD), Prolonged Pr Interval (LPR), Prolonged Qr Interval (LQT), T Wave Abnormal (Tab), T Wave Inversion (Tinv), Left Bundle Branch Block (LBBB), Qwave Abnormal (Qab), and Ventricular Premature Beats (VPB). Figure 3 shows samples from each of the 27 ECG signal classes.

4. Proposed Model

This paper proposes a ResNet model with four databases to classify ECG signals. This section starts by presenting the architecture of model proposed and then highlighting our working method.

4.1. Proposed Model Architecture. In this paper, ResNet-50 is the proposed model for features extraction. In fact, it combines convolutional neural network for ECG diagnoses. Figure 4 illustrates an overview of the model architecture. Making the model training tractable has been assured by the residual blocks with shortcut connections. As input, the model takes an ECG signal $x \in \mathbb{R}^{n_{\text{samples}} \times 12}$. As outputs, the result of the multilabel classification is $\hat{y} \in \mathbb{R}^{1 \times 27}$.

A 1D convolution layer (conv1D) was applied to these inputs, a batch normalization layer (BN), a rectified linear unit activation layer (ReLU), and a Max Pooling layer. Also, 16 residual blocks have been used to extract deep features. There are two types of residual blocks as follows:
Figure 3: Continued.
Res_Block_1 is composed of three Conv1d layers, three BatchNorm1d layers, and two ReLU activation layers. On the one hand, one Conv1d layer and one BatchNorm1d layer are used to match dimensions and skip connections on the other.

Res_Block_2 is composed only of three Conv1d layers, three BatchNorm1d layers, and two ReLU activation layers. The Conv1d layers are used for extracting features and the BatchNorm1d layers are used to make the model faster and stable. The ReLU layers are introduced to perform nonlinear activation. The features extracted by the residual blocks are pooled using Average Pooling, where the pooling results are collected and sent to the output layer, which uses the sigmoid activation function to produce predictions.

4.2. Dataset Characteristics. The used dataset in this work combines four public databases containing 42,511 recordings of 12-lead ECG. This type of ECG is the most used in clinical cases because of the large amount of information that it generates. These recordings are sampled at a frequency of 500 Hz. Table 2 describes the characteristics of each database.

The used dataset in this work contains 27 classes, where 26 classes are of CVDs and a class represents a normal heart state. Figure 5 shows the distribution of these classes on each database. Figure 6 illustrates an overview of its distribution in the dataset where a problem of data imbalance and data insufficiency are noticed.

4.3. Simulation Workflow. Figure 7 illustrates the workflow of the proposed method that has been implemented in our study. Each step of this workflow will be explained in the following subsections.

4.3.1. Data Preprocessing. The length of the signals of the four databases varies from 6 seconds to 60 seconds. Therefore, it has been decided to uniform all the lengths. Since the common length is 10 seconds, we set 5000 samples (10 s, 500 Hz as sampling rate). For ECGs recordings having a duration superior to 10 seconds, the first 10 s was kept. Otherwise, signals will be zero-padded until having 10 s as a duration. Figure 8 describes this preprocessing technique, where in this step, for the signal counting less than 5000 samples will be zero-padded to obtain 5000 samples. For signals containing more than 5000, samples above this value will be discarded.

Figure 9 demonstrates in more detail the technique of uniformly reducing the length of an ECG signal, in which we have a signal with a length of 7500 reduced to 5000 to train our model. Data preprocessing is explained as per Algorithm 1.
Figure 4: Presentation of the proposed model.
4.3.2. Data Augmentation. As shown in Figures 4 and 5, the problem of data insufficiency and data imbalance is serious for CVDs. To deal with this issue, amplitude scaling was applied as a data augmentation technique. The creation of realistic data to prevent data scarcity is known as data augmentation. Practically, it enhances the model robustness and lessens the fitting concerns against similar examples [14]. Amplitude scaling is the multiplication of ECG signals by a random factor $\alpha$. This technique aims to compress or stretch the magnitude. The factor $\alpha$ is sampled from normal

$$
\begin{array}{llll}
\text{Database} & \text{Sources} & \text{Number of ECG recordings} & \text{Length of ECG recordings} \\
\text{CPSC 2018 [7]} & \text{China Physiological Signal Challenge in 2018} & (i) M: 3699 & 6 \text{s–60 s} \\
& & (ii) F: 3178 & \\
\text{CPSC 2018 EXTRA [7]} & & (i) M: 1843 & 6 \text{s–60 s} \\
& & (ii) F: 1610 & 21,837 \\
\text{PTB-XL [8]} & \text{Physikalisch Technische Bundesanstalt} & (i) M: 11,379 & 10 \text{s} \\
& & (ii) F: 10,458 & 10,344 \\
\text{Georgia [7]} & \text{Georgia} & (i) M: 5551 & 10 \text{s} \\
& & (ii) F: 4793 & \\
\end{array}
$$

| Pathology | CPSC 2018 | CPSC 2018 - Extra | PTB-XL | Georgia |
|-----------|-----------|--------------------|--------|---------|
| IAVB (2394) | 722 | 106 | 797 | 769 |
| AF (3458) | 1221 | 153 | 1514 | 570 |
| AFL (313) | 0 | 54 | 73 | 186 |
| Brady (277) | 0 | 271 | 0 | 6 |
| CRBBB (683) | 0 | 113 | 542 | 28 |
| IRBBB (1611) | 0 | 86 | 1118 | 407 |
| LAnFB (1806) | 0 | 0 | 1626 | 180 |
| LAD (6086) | 0 | 0 | 5146 | 940 |
| LBBB (1041) | 236 | 38 | 536 | 231 |
| LQSV (556) | 0 | 0 | 182 | 374 |
| NSIVCB (996) | 0 | 4 | 789 | 203 |
| PR (299) | 0 | 3 | 296 | 0 |
| PAC (1726) | 616 | 73 | 398 | 639 |
| PVC (188) | 0 | 188 | 0 | 0 |
| LPR (340) | 0 | 0 | 340 | 0 |
| LQT (1513) | 0 | 4 | 118 | 1391 |
| QA (1013) | 0 | 1 | 548 | 464 |
| RBBB (2400) | 0 | 1 | 343 | 83 |
| RAD (427) | 0 | 1 | 343 | 83 |
| SA (1238) | 0 | 11 | 772 | 455 |
| SB (2359) | 0 | 45 | 637 | 1677 |
| SNR (20766) | 918 | 4 | 18092 | 1752 |
| STach (2390) | 0 | 303 | 826 | 1261 |
| SVPB (211) | 0 | 33 | 157 | 1 |
| TAb (4673) | 0 | 22 | 2345 | 2306 |
| TInv (1111) | 0 | 5 | 294 | 812 |
| VPB (365) | 0 | 8 | 0 | 357 |

Figure 5: Pathologies distribution in each database.
Figure 6: Histogram of pathology distribution in the dataset.

Figure 7: Work methodologies.

Figure 8: Preprocessing technique.
distribution $N(1, 0.1)$. The algorithm of amplitude scaling algorithm is shown in Algorithm 2.

4.3.3. Data Split (Train, Validation, Test). As mentioned in Section 4.2 the dataset used comprises 42,511 ECG records. First, dataset has been split into two sets: test set and training and validation set in the ratio of 0.75 : 0.25. After this, 10-fold stratified cross-validation approach on the training and validation set was applied. This will return 10 stratified folds. These folds will be made by preserving the percentage of samples for each class. This forces the class distribution in each data split to match the distribution in the whole training dataset.

Generally, the training data is dedicated to train the model. The validation data is reserved for optimizing the model. Therefore, a search for the best parametrization without using the test data is done to measure the model performance and allow us to evaluate the model generalization ability. Finally, we obtain a test set and training and validation with 10,627 and 31,884 ECG records, respectively. In addition, the shapes of each training fold and validation fold are 25,507 and 6377 ECG records, respectively. Figure 10 illustrates an overview of this proposed method.

4.3.4. Training and Evaluation. The trial-and-error approach is used to determine the hyperparameters. In essence,
Adam with a learning rate of $10^{-3}$ is employed as the optimizer. The binary cross-entropy loss function was used. The optimal values of the hyperparameters of the deep neural network are as follows: the length of the 12-lead ECG input is set to 5000, the batch size is 32, and the number of epochs is equal to 100.

To reduce the learning rate, we used the learning rate scheduler with the following schedule:

$$\text{lr} = \begin{cases} \text{lr}, & \text{epoch} < 10, \\ \text{lr} \cdot e^{-0.1}, & \text{epoch} \geq 10. \end{cases}$$

4.4. Evaluation Metric. In multiclassification problems, precision and accuracy are commonly used to assess the model's performance. The performance of an algorithm is often measured in terms of four variables for each record. These two performance indicators (accuracy and precision) can be calculated in equations (2) and (3)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN},$$

$$\text{Precision} = \frac{TN}{TN + FP}.$$  

where TP denotes True Positive, FP denotes False Positive, TN denotes True Negative, and FN denotes False Negative.

5. Results and Discussion

This section presents visual and descriptive discussion based on the proposed model. Additionally, a comparative table has been introduced to compare the proposed work against other studies cited in related works as per Table 3. To note, OVH Cloud has been used with the following characteristic, to train the proposed model.

(i) Memory: 45 Go
(ii) vCore: 8
(iii) GPU: NVIDIA Tesla V100 16 Go

Precision and accuracy are generally used as two performance indicators to evaluate model performance in multiclassification model. In our situation, precision represents the probability that the model makes the correct prediction, while accuracy is defined as the ratio between the proportion of correct predictions made by the model and the number of total predictions.

In the training and validation phase, the obtained accuracy is 97.63% and 97.58%, respectively. In terms of precision, we obtained 89.67% and 88.85%, respectively. The loss value indicates how well or poorly the proposed model performs after each iteration. For the loss, $3.10^{-3}$ and $1.27 \times 10^{-2}$ for each phase were reached as can be seen in Table 4.

Because of using stratified 10 folds in the data-splitting step, in the transition from fold to another, the model undergoes a disorder until the stabilization in the last fold. We can observe that, after the 60th iteration, the model progressively converges to reach a stable accuracy, precision, and loss at the 100th iteration. Figures 11–13 demonstrate the evolution of these performance metrics.

It is important for disease diagnosis to improve performance metrics for the correct classification of cardiovascular diseases. ResNet-50 shows better classification performance in comparison to the other studies cited in related works as can be seen in the comparative Table 3.

In the evaluation of the proposed model performance, a normalized confusion matrix was created as can be seen in Figure 14, where each row refers to an actual class, while each column represents a predicted class. The proposed model performs well for NSR, RBBB, STach, TInv, AF, IRBBB, and LBBB classes. Next comes NSIVCB, IAVB, LanFB, AFL, and RAD where the percentage of correct predictions is higher than 60%. For the rest of the classes, like QAb, LAD, and LPR, PR, the model performs badly. This problem of lower predictions is due to the data imbalance even though an amplitude scaling was applied.
Table 3: Results obtained by different research in relation to the proposed work.

| Author                 | Year | Number of records | Model          | Preprocessing | Number of classes | Accuracy (%) | Precision (%) |
|------------------------|------|-------------------|----------------|---------------|-------------------|--------------|---------------|
| Antonio et al. [34]    | 2020 | 2,322,513         | DNN            | No            | 6                 | 92.36        |               |
| Ahsanuzzman et al. [35]| 2020 | 48                | LSTM and RNN   | Yes           | 1                 | 97.57        |               |
| Obeidat et al [36]     | 2021 | 2000              | CNN and LSTM   | Yes           | 6                 | 98.22        | 98.26         |
| Adedinsewo et al. [38] | 2020 | 6613              | CNN            | No            | 1                 | 85.9         | 74            |
| Xiong et al. [39]      | 2020 | 8528              | ResNet-16      | Yes           | 4                 | 82           |               |
| Dongdong et al. [19]   | 2021 | 6877              | ResNet-34      | Yes           | 9                 | 96.6         |               |
| Proposed work          | 2021 | 42,511            | ResNet-50      | Yes           | 27                | 97.63        | 89.67         |

Table 4: Results of the proposed method.

| Performance | Training phase | Validation phase |
|-------------|----------------|------------------|
| Accuracy    | 97.63%         | 97.58%           |
| Precision   | 89.67%         | 88.85%           |
| Loss        | $3.10^{-3}$    | $1.27.10^{-2}$   |

Figure 11: Evolution of training and validation accuracy.

Figure 12: Evolution of training and validation precision.
Figure 13: Evolution of the loss in the training and validation.

Table 5: Test results by the model proposed.

|       | Test 1                                      | Test 2                                      |
|-------|---------------------------------------------|---------------------------------------------|
| Samples | ![Graph](image1.png)                       | ![Graph](image2.png)                       |
| Incorrect | ![Incorrect Prediction](image3.png) | ![Incorrect Prediction](image4.png) |
| Predicted: Sinus Rhythm | Actual: sinus bradycardia | Predicted: 1st Degree AV Block | Actual: left bundle branch block |
|       | ![Graph](image5.png)                       | ![Graph](image6.png)                       |
| Samples | ![Graph](image7.png)                       | ![Graph](image8.png)                       |
| Correct | ![Correct Prediction](image9.png)          | ![Correct Prediction](image10.png)         |
| Predicted: Sinus Rhythm | Actual: sinus rhythm | Predicted: Atrial Fibrillation | Actual: atrial fibrillation |
Table 5 shows the test results of the proposed model including the incorrect samples (Tests 1 and 2) and correct (Tests 3 and 4) samples that were detected by our model, as well as its prediction and the current state of the ECG.

6. Conclusion and Future Work

An effective DL approach based on ResNet-50 has been presented in this paper to classify CVDs. The number of classes that have been considered were 27, where 26 belong to heart anomalies and 1 belongs to normal state. The dataset used in this study combines four datasets collected from three different countries. The achieved results proved the feasibility and the efficiency of the proposed model. The results, also, have been compared and validated against values in the recent published literature. However, the proposed model suffers from high computational complexity and low range of interpretability. Thus, as future research, the proposed approach will be improved to be ideally adapted for wider range of different healthcare applications.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

This research was funded by the Deanship of Scientific Research at Taif University, Kingdom of Saudi Arabia, Taif, University Researchers Supporting Project no. TURSP-2020/265.

References

[1] J. Emelia, S. S. V. Benjamin, W. Clifton et al., “Heart disease and stroke statistics—2018 update: a report from the American heart association,” Circulation, vol. 137, pp. e67–e492, 2018.

[2] Z. I. Attia, P. A. Noseworthy, F. Lopez-Jimenez et al., “An artificial intelligence-enabled ECG algorithm for the
identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction,” *The Lancet*, vol. 394, no. 10201, pp. 861–867, 2019.

[3] R. C. Schlant, R. J. Adolph, J. F. DiMarco et al., “Guidelines for electrocardiography: a report of the American College of Cardiology/American heart association task force on assessment of diagnostic and therapeutic cardiovascular procedures (committee on electrocardiography),” *Journal of the American College of Cardiology*, vol. 19, pp. 473–481, 1992.

[4] R. B. Schnabel, X. Yin, P. Gona et al., “50 year trends in atrial fibrillation prevalence, incidence, risk factors, and mortality in the Framingham Heart Study: a cohort study,” *The Lancet*, vol. 386, no. 9989, pp. 154–162, 2015.

[5] W. G. Morrison and I. J. Swann, “Electrocardiograph interpretation by junior doctors,” *Emergency Medicine Journal*, vol. 7, no. 2, pp. 108–110, 1990.

[6] F. A. Almalki, S. Ben Othman, F. A. Almalki, and H. Sakli, “EERP-DPM: energy efficient routing protocol using dual prediction model for healthcare using IoT,” *Journal of Healthcare Engineering*, vol. 2021, Article ID 9988038, 15 pages, 2021.

[7] A. L. Goldberger, L. A. N. Amaral, L. Glass et al., “PhysioBank, PhysioToolkit, and PhysioNet: PhysioBank, PhysioToolkit, and PhysioNet,” *Circulation*, vol. 101, no. 23, 2000.

[8] P. Wagner, N. Strodthoff, and R. D. Boussejolt, *PTB-XL, a Large Publicly Available Electrocardiography dataset, Scientific Data*, vol. 7, no. 154, 2020.

[9] Y. Wu, H. Guo, C. Chakraborty, M. Khosravi, S. Berretti, and S. Wan, “Edge computing driven low-light image dynamic enhancement for object detection,” *IEEE Transactions on Network Science and Engineering*, p. 1, 2022.

[10] E. Jing, H. Zhang, Z. G. Li, Y. Liu, Z. Ji, and I. Ganchev, “ECG heartbeat classification based on an improved ResNet18 model,” *Computational and Mathematical Methods in Medicine*, vol. 2021, Article ID 6649970, 13 pages, 2021.

[11] M. Gowri Shankar and C. Ganesh Babu, “An exploration of ECG signal feature selection and classification using machine learning techniques,” *International Journal of Innovative Technology and Exploring Engineering*, vol. 9, 2020.

[12] A. Rajkumar, M. Ganesan, and R. Lavanya, “Arrhythmia Classification on ECG Using Deep Learning,” in *Proceedings of the 2019 5th International Conference on Advanced Computing and Communication Systems (ICACCS)*, pp. 365–369, IEEE, Coimbatore, India, March 2019.

[13] V. Acharya, V. Ravi, T. D. Pham, and C. Chakraborty, “Peripheral blood smear analysis using automated computer-aided diagnosis system to identify acute myeloid leukemia,” *IEEE Transactions on Engineering Management*, pp. 1–14, 2021.

[14] H. Alqurana, A. M. Alqudah, I. Abu-Qasmieh, A. Al-Badarneh, and S. Almasahqbeh, “ECG classification using higher order spectral estimation and deep learning techniques,” *Neural Network World*, vol. 29, no. 4, pp. 207–219, 2019.

[15] A. M. Alqudah, S. Qazan, L. Al-Ebbini, H. Alqurana, and I. Abu Qasmieh, “ECG heartbeat arrhythmias classification: a comparison study between different types of spectrum representation and convolutional neural networks architectures,” *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–31, 2021.

[16] A. M. Alqudah, A. Albadanah, I. Abu-Qasmieh, and H. Alqurana, “Developing of robust and high accurate ECG beat classification by combining Gaussian mixtures and wavelets features,” *Australasian Physical & Engineering Sciences in Medicine*, vol. 42, no. 1, pp. 149–157, 2019.

[17] D. Zhang, X. Yuan, P. Zhang, and S. Yang, “Interpretable deep learning for automatic diagnosis of 12-lead electrocardiogram,” *Science*, vol. 24, 2021.

[18] D. Jia, W. Zhao, J. Hu, H. Wang, C. Yan, and Z. Li, “Detection of first-degree atrioventricular block on variable-length electrocardiogram via a multimodal deep learning method,” in *Proceedings of the 2019 Computing in Cardiology (CinC)*, September 2019.

[19] R. He, Y. Liu, K. Wang et al., “Automatic cardiac arrhythmia classification using combination of deep residual network and bidirectional LSTM,” *IEEE Access*, vol. 7, 2019.

[20] R. Boussejlot, D. Kreiseler, and A. Schnabel, “Nutzung der EKG-Signaldatenbank CARDIODAT der PTB über das Internet,” *Biomedizinische Technnik*, p. 1, 1995.

[21] W. Liu, M. Zhang, Y. Zhang et al., “Real-time multilead convolutional neural network for myocardial infarction detection,” *IEEE Journal of Biomedical and Health Informatics*, vol. 22, 2017.

[22] H. Bhuyan, D. C. Chakraborty, S. Pani, and V. Ravi, “Feature and subfeature selection for classification using correlation coefficient and fuzzy model,” *IEEE Transactions on Engineering Management*, pp. 1–15, 2021.

[23] J. Zhang, F. Lin, P. Xiong et al., “Automated detection and localization of myocardial infarction with stacked sparse autoencoder and TreeBagger,” *IEEE Access*, vol. 7, 2019.

[24] A. Selvalingam, M. Alhusseini, A. J. Rogers et al., “Developing convolutional neural networks for deep learning of ventricular action potentials to predict risk for ventricular arrhythmias,” *Circulation*, vol. 140, 2019.

[25] S. W. Smith, B. Walsh, K. Grauer et al., “A deep neural network learning algorithm outperforms a conventional algorithm for emergency department electrocardiogram interpretation,” *Journal of Electrocardiology*, vol. 52, pp. 88–95, 2019.

[26] Y. Li, Y. Pang, K. Wang, and X. Li, “Toward improving ECG biometric identification using cascaded convolutional neural networks,” *Neurocomputing*, vol. 391, pp. 83–95, 2020.

[27] Y. Zhang, Z. Xiao, Z. Guo, and Z. Wang, “ECG-based personal recognition using a convolutional neural network,” *Pattern Recognition Letters*, vol. 125, pp. 668–676, 2019.

[28] U. R. Acharya, H. Fujita, S. L. Oh et al., “Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals,” *Applied Intelligence*, vol. 49, no. 1, pp. 16–27, 2019.

[29] N. Iyengar, C.-K. Peng, R. Morin, A. L. Goldberger, and L. A. Lipsitz, “Age-related alterations in the fractal scaling of cardiac interbeat interval dynamics,” *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, vol. 271, pp. 1078–1084, 1996.

[30] D. S. Baim, W. S. Colucci, E. S. Monrad et al., “Survival of patients with severe congestive heart failure treated with oral milrinone,” *Journal of the American College of Cardiology*, vol. 27, no. 1, p. 1986.

[31] P. Wang, B. Hou, S. Shao, and R. Yan, “ECG arrhythmias detection using auxiliary classifier generative adversarial network and residual network,” *IEEE Access*, vol. 7, 2019.

[32] S. Hadiyoso, K. Usman, and A. Rizal, “Arrhythmia detection based on ECG signal using android mobile for athlete and patient,” in *Proceedings of the 2015 Third International Conference on Information and Communication Technology (ICOICT)*, pp. 166–171, Nusa Dua, Bali, Indonesia, May 2015.

[33] F. Murat, O. Yildirim, M. Talo, U. B. Baloglu, Y. Demir, and U. R. Acharya, “Application of deep learning techniques for
heartbeats detection using ECG signals—analysis and review,” *Computers in Biology and Medicine*, vol. 120, 2020.

[34] A. H. Ribeiro, M. H. Ribeiro, G. M. M. Paixão et al., “Automatic diagnosis of the 12-lead ECG using a deep neural network,” *Nature*, vol. 11, 2020.

[35] S. M. Ahsanuzzaman, T. Ahmed, and M. Atiqur Rahman, “Low Cost, Portable ECG Monitoring and Alarming System Based on Deep Learning,” in *Proceedings of the 2020 IEEE Region 10 Symposium (TENSYMP)*, IEEE, Dhaka, Bangladesh, June 2020.

[36] Y. Obeidat and A. M. Alqudah, “A hybrid lightweight 1D CNN-LSTM architecture for automated ECG beat-wise classification,” *Traitement du Signal*, vol. 38, no. 5, pp. 1281–1291, 2021.

[37] F. A. Almalki and B. O. Soufiene, “EPPDA: an efficient and privacy-preserving data aggregation scheme with authentication and authorization for IoT-based healthcare applications,” *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 5594159, 18 pages, 2021.

[38] D. Adedinsewo, R. E. Carter, Z. Attia et al., “An artificial intelligence-enabled ECG algorithm to identify patients with left ventricular systolic dysfunction presenting to the emergency department with dyspnea,” *Nature Medicine*, vol. 9, pp. 707–715, 2020.

[39] Z. Xiong, M. K. Stiles, and J. Zhao, “Robust ECG signal classification for detection of atrial fibrillation using a novel neural network,” in *Proceedings of the 2017 Computing in Cardiology (CinC)*, Rennes, France, September 2017.