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Deep Learning Model for Securing IOT Configurations for End-to-End Data Authentication

Ridhdhi Marmik Naik

HOD

Department of Computer Science Engineering

Bhagwan Mahaveer College of Engineering & Technology, Surat

Corresponding Author's Email: *- ridhdhi.naik@bmusurat.ac.in*

Abstract

Compared to other biometrics, electrocardiograms (ECGs) have gained widespread acceptability as mediums for validating animations in numerous security applications, especially in new and emerging technologies. Our study utilizes this important trait to advance available machine and deep learning ECG authentication systems by leveraging the use of Fog computing servers that offer connection to Internet of Things (IoT) devices while maintaining access to computational and storage resources. Specifically, in our proposed technique, the preprocessing, feature extraction and classification routines are combined into one unit, while individual ECG signals from the database are directly fed into a convolution neural network (CNN) model and subsequently classified as an accepted or unaccepted (i.e., rejected) class. Additionally, we tailor our authentication system as a cost-efficient one focused on reducing latency, which makes it ideal for applications on Fog computing platforms. To validate our proposed model, we applied it on standard ECG signals from the Physikalisch-Technische Bundesanstalt (PTB) database where outcomes of 99.50%, 99.73%, 100%, and 99.78%, respectively that are reported for accuracy, precision, recall, and F1-score indicate the tenability of deploying our technique in real-time authentication systems. Furthermore, we present discussions regarding the performance of the model relative to recent techniques that are built on traditional machine and deep learning techniques.

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Keywords:-*Deep Learning, Biometric identification. ECG, Information Security, IoT, Fog computing, Industrial Data Integration*

INTRODUCTION

Recently, increases in incidents of counterfeiting have forced a scale down in the acceptability of traditional authentication methods such as security tokens, passwords; personal identification numbers (PINs), etc. Instead, the use of biometric identification. is now prevalent. Even so, traditional biometric markers such as fingerprint, face recognition, iris recognition and ear recognition are susceptible to Influences of wide-ranging factors such as universality, uniqueness, performance, measurability, acceptability, circumvention, etc. [1]. In addition to providing good compromise in these factors and unlike the traditional biometric modalities, such as fingerprints, which do not always imply consciousness, the use of electrocardiogram (ECG) signals as biometric markers provides a good test of animations.

The ECG measures the rhythm associated with the pumping of blood in and out of the heart [2]. Recently, available ECG sensors have become smaller in size, which makes it easier to integrate them into wearable devices and connected vehicles [3]. Additionally, minimal computation and template size are among other reasons attributed to the popularity and utility of ECGs in different fields [4, 5]. In [6], these properties are exploited for the secure identification of drivers and passengers in vehicle access control.

Meanwhile, the ECG is considered pivotal in the diagnosis of various cardiac conditions, including arrhythmias, and other coronary disorders. A typical cardiac cycle of an ECG signal comprises a P-wave, a QRS-complex, and a T-wave [2]. In addition, there are three essential segments or intervals known as ST-segment or ST-interval, PR-segment or PR-interval, and QT-interval. The atria depolarization caused by atria contraction is traced as P-wave while ventricular depolarization or contraction is indicated by the QRS-complex segment. Afterward, both ventricles come back to relaxation states, which are known as T-wave [7]. The PR-interval, which is also known as the PR-segment, is the line between the start of the P-wave and the Q-wave, whereas the QT-interval is the line between the start point of the QRS-complex and that of the T-wave. Similarly, the ST-interval, which is also known as the

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ST-segment, is the line between S-wave and T-wave. Fig. 1 illustrates a typical ECG signal as well as its peaks and intervals. These characteristics have been utilized in wide-ranging applications, including improvement of security in body-area network sensors (BANs) such as smart wristbands and heart pacemakers [8].

Lately, there has been an upsurge in the use of these signals in applications across different medical Internet of Things (IoT) platforms [9]. However, there is still a shortage of such applications using ECG for authentication [10]. Meanwhile, whereas cloud computing approaches are more widespread for handling IoT applications, they are known to suffer from high latency to applications, impact of considerable traffic overhead, etc., all of which are detrimental to real-time and delay-sensitive applications [11]. Unlike these past efforts, our study presents a deep learning-based ECG authentication approach for Fog computing platforms where, unlike in IoT, cloud resources and services are moved to edge nodes [12].

Broadly speaking, previous studies on ECG-based authentication can be classified as either conventional machine learning techniques [13–16] or deep learning-based approaches [17–23]. In the former, the ECG signals pass through many steps (typically for preprocessing of the ECG data, extracting and selecting the ECG features and classification) before the authentication is accomplished. These steps complicate and overburden the targeted authentication process.

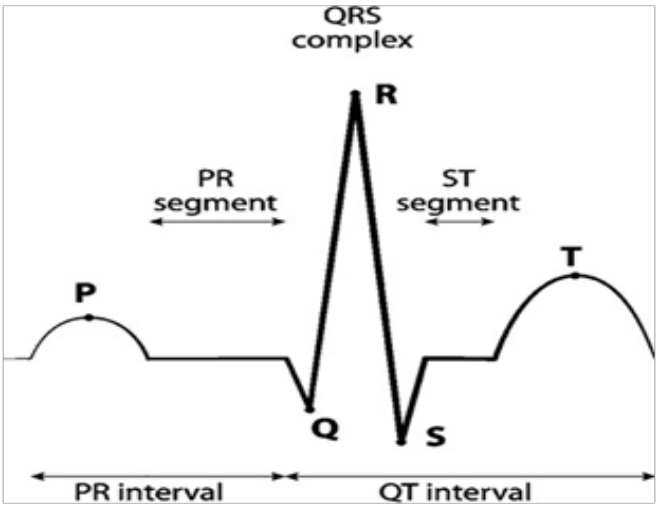


Fig. 1 Illustration of all peaks and intervals on an ECG signal [20].

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Moreover, most of these approach Reported below-par authentication performance when working on other To overcome these limitations, we propose a deep learning model (DLM) approach to human authentication system using ECG signals. As one of its many upsides, DLM techniques subsume many of the earlier mentioned steps of traditional machine learning approaches.

Deep learning is a class of machine learning where networks are capable of unsupervised learning from unstructured or unlabeled data. These networks facilitate the gradual extraction of higher-level features from raw input data. The most widespread used DLM method, known as convolution neural network (CNN), has its origins and best performance in image analysis [24]. Recently, CNN-based DLMs have become popular across many fields including medicine [25–28], computer vision [29–32], remote sensing [33, 34], and many other interesting applications [35–38].To encapsulate, whereas the use of DLMs in biometric identification. Particularly CNN [39] is not new; very few of these methods are based on ECG authentication [17–23]. Even so, they are encumbered by the following shortcomings.

databases as well as when evaluated on larger datasets that over fitting had been reported [13–16].

- Temporal and resource overhead associated with the need for preprocessing, segmentation and, QRS detection stages (as in [13–16]).
- Sensitivity to quality of ECG signals (as in [17–19]).
- Need for a separate classifier for authentication, which complicates the already complex process [20–23].
- Working on more than one lead ECG, which imposes additional hardware susceptibility (as in [17, 20]).

To ameliorate the enumerated deficiencies of both the machine and deep learning approaches, our proposed method presents the following contributions.

- An efficient CNN-based DLM is proposed to automatically authenticate the ECG signals for efficient identity validation.
- Since ECG data suffer from various noise artifacts due to unconstrained signaling environments and considering the challenges of collecting all in one environment, this study employs an end-to- end DLM to eliminate the need for a preprocessing stage.

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- An edge-computing framework is integrated into the proposed model as a cost-efficient remedy to lower latency wherein storage and processing capabilities are provided at the edge of the radio access network that is in close proximity to mobile users. Consequently, our strategy facilitates real-time and delay-sensitive applications for execution.

As noted earlier, there has been a recent surge in the integration of IoT and wireless technologies into a wide range of systems such as healthcare, pattern recognition, industry [39–41]. These devices including sensors are infused in automatic car tracking adapters, Google Glass, blood glucose monitors, ECGs, continuous glucose monitors, oximeters, insulin pens, temperature monitors, etc. Correspondingly, numerous applications and multimedia services that require supplementary computations and high data communication are increasing rapidly. Nevertheless, these applications are still resource-limited with restricted computational power and energy.

Fog computing, which is described as a network architecture that provides computing and data storage at edge server nodes [12], is considered a solution that can address the limitations of individual devices. Moreover, it is known to offer lower latency and high bandwidth [12], which supports its implementation in real-time applications. Consequently, computationally intensive services of IoT devices can be offloaded and executed on this server through a wireless channel. This will mitigate the load demand while also helping to extend battery life [12].Our study advances previous machine and deep learning ECG authentication efforts by leveraging the use of Fog computing servers that can be connected to IoT devices while maintaining access to computational and storage resources. Fig. 2 illustrates the integration of ECG authentication in a car control system which is considered a daily life application. First, the user’s ECG signal is acquired and sent to the Fog computing server through mobile devices where the proposed model is trained, andrelevant data are stored. Next, if the user is authenticated, the edge server will send an automated signal to the car sensor which transfers further control to the user. Otherwise, the edge server will reject the user’s request and subsequently alert appropriate authorities to prevent the vehicle from being stolen.Therefore, the overall performance of these systems is improved since computationally-intensive

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operations of the model are processed at the edge server.Table 1 presents a definition of parameters used in this example and subsequent sections of this study.The rest of this paper is structured as follows. In Section 2, we present the outline and other details of our proposed CNN model whose validation via a range of performance evaluation experiments are presented in Section 3. These results are subsequently analyzed and discussed alongside related work in Sections 4 and 5, respectively.

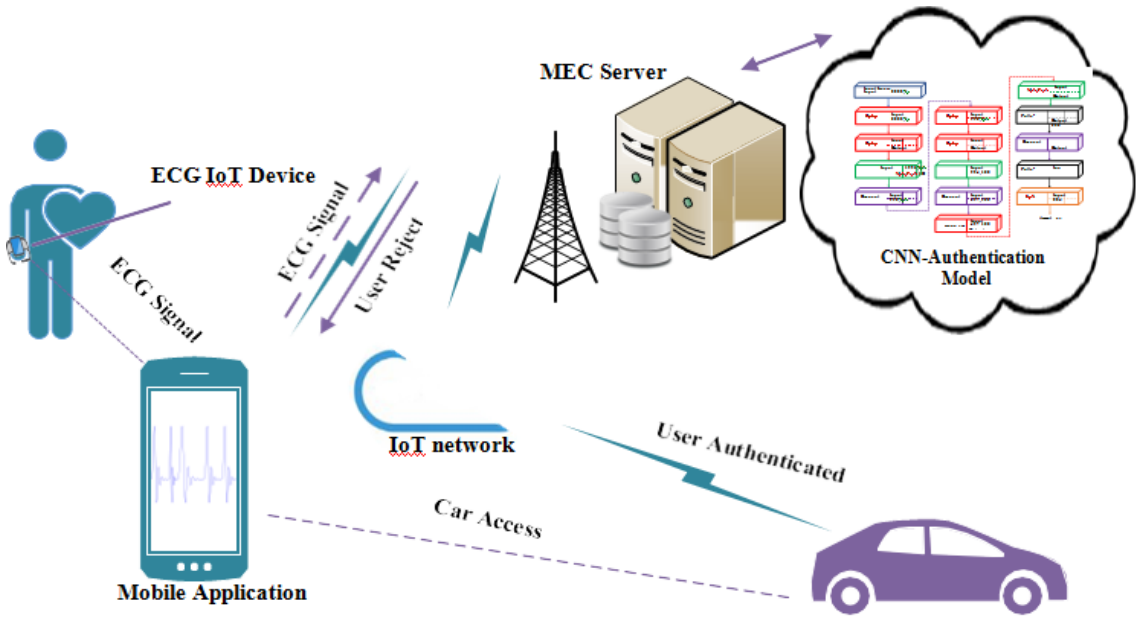


Fig. 2. Integration of ECG authentication in a car control system.

Table 1. Definition of parameters

Parameter	Definition
N	Element number or the number of sets applied in the 5-fold
X	Signal
F	Filter in the input signal (x)
P	Precision
R	Recall
EEE	Equal error rate
ROC	Receiver operating characteristic
F1	F1-score
FP	False positive
FN	False negative
TP	True positive
TN	True negative
M	Number of classes

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Related Works

As highlighted in our introduction, previous studies on ECG-based authentication can be broadly classified as either classical machine learning (CLM)-based techniques [13–16, 42] or DLM-based approaches [17–23, 43–47]. This section provides an overview of recent studies in both categories.

Classical Machine Learning-based Techniques

Classical machine learning (CLM) refers to techniques that pass through all steps of the machine learning pipeline [48]. In this kind of system, the ECG signals pass through many steps before the authentication is accomplished. The first stage entails removal of noise and other artifacts while also enhancing the input ECG signals in order to make them suitable for further processing. This step is usually called the preprocessing step.

The second step is focused on extracting and selecting the prominent features from the preprocessed ECG signal. These features should be unique for each signal and thisstep is called feature extraction step. Finally, the features are fed into the classifier in the classification step where the authentication is done.

Most CLM techniques adopt basic frameworks outlined above. For instance, in [13], the authors introduced a feature extraction and a continuous authentication method by proposing one-dimensional multi-resolution local binary patterns (1DMRLBP) and sequential sampling feature extraction for one- dimensional signals. This system updates decision thresholds and sample sizes during run-time. As reported in [13], it accounts for the quantization error needed to tolerate noise and extracts local and global signal morphology.

For validation, the authors reported using data from 290 subjects from the Physikalisch-Technische Bundesanstalt (PTB) database and recorded an equal error rate (EER) of 10.10% for ECG signal authentication. Similarly, Safi et al. [14], presented a feature extraction approach that they called pulse active ratio (PAR) for ECG-based authentication using ECG fiducially points as a feature vector. In this scheme, each feature vector from the test dataset is compared to all feature vectors in the training database with Euclidean distance set as the similarity measurement to generate matching scores. If the feature vectors from the test and training dataset are the same, the authentication is considered successful. They reported

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experiments involving 112 individuals from the PTB dataset of which they reported that 98 individuals exhibited arrhythmia beats while the remainder were healthy. They also recorded an EER of 9.89 % and 19.15% for normal and arrhythmia beats, respectively. In their contribution, Goshvarpour and Goshvarpour [42], developed an expert system for human authentication based on ECG signals.

They executed their authentication protocol by combining the ECG characteristics with information theoretic (IT) considerations. In the last step, using 5-fold cross-validation, they applied k-nearest neighbor (kNN) to identify individuals and reported an average accuracy of 97.6%. In their contribution, Ivanciu et al. [49], presented an ECG-system based on Siamese neural networks for authentication.

They used the Siamese network to simplify the training process. In addition, they deployed the system on private cloud to ensure its security and scalability. They reported a sensitivity of 87.3% and overall accuracy of 86.47%. In [50], the authors introduced an ECG authentication system based on incremental learning to identify the ECG signal of each subject under several conditions. They employed support vector machine (SVM) for authentication and reported the best accuracy of 99.4%. Similarly, in [51], the authors presented an ECG authentication system based on nonlinear normalization according to various physiological conditions. They reported an accuracy of 99.05% and 88.14% for resting and non-resting conditions, respectively.

To conclude, we also note that despite the performance recorded, authentication performance in most of the highlighted CLM studies, are below-par when working on other databases or when assessed on large datasets, which also leads to over fitting. Exploiting their potency, nowadays, DLMs have been proposed to overcome most of the problems faced by CLM methods across different domains and applications as highlighted in the sequel.

Security Scenarios with CNN-based DLMs

Deep learning is widely regarded as the advanced solution to most machine learning problems. As reviewed earlier, most DLM are built on CNNs, and they are credited with some of the stellar performance recorded in various fields including biometric identification.. For

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example, in [17], the authors used CNN to deploy an authentication algorithm based on more than one ECG lead. Theiralgorithm recorded an EER of 1.36% for authentication using the PTB database. In [18], the authors presented a CNN-based multi-modal authentication system based on ECG and fingerprints. Their technique used a pre-trained VGG-Net model and transfer learning technique by using the output of the last fully connected layer as features for the input ECG image. Following this, an improved version of bio-hashing strategy [16] was employed to protect the features.

Finally, an external classifier called Q-Gaussian multiclass support vector machine (QG-MSVM) was used for authentication. They reported an EER of 3.20% for the PTB database.Furthermore, in [19] the authors used CNN to generate ECG features that they protected using matrix operations [16]. In the end, they employed a separate classifier (QG-MSVM) for authentication and reported an EER of 3.5% using images in the PTB database. In another effort, Hammed et al. [20] combined machine learning features with deep learning features of ECG for human authentication using CNN. They employed scan and removal techniques to extract the ECG features and CNN for classification. They recorded an EER of 1.63% for ECG authentication. In their contribution, Chu et al.[23] used the parallel multi-scale one-dimensional residual network for ECG authentication. Specifically, in the preprocessing step, they located the R-peak and used it with the whole ECG signal to extract the feature. After that, they used a residual network with a new loss function to extract the features and train the network. They used all records in the PTB database and reported an EER of 0.59%.Similarly, Zhang et al. [43] presented a wavelet domain multire solution CNN (MCNN) for ECG identification.

The first step of their technique used blind segmentation to process the data and process first blind segmentation and applied an auto-correlation operation on the transformed data to remove the difference resulting from the use of randomly chosen signal segments.

They reported an average identification accuracy of 93.5%. Similar to that effort, Abdeldayem and Bourlai [44], presented a human identification system based on ECGs where the input signal was segmented to enrich its original informational content. Subsequently, they generated spectral correlation images that

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were fed to the CNN for identification. They reported an accuracy of 95.6% with false acceptance and rejection rates of 0.2% and 0.1%, respectively. Similarly, in [45], the authors presented a CNN protocol for human identification based on ECG. They employed two CNN models, one for feature extraction and another for identification a combination that recorded an average identification accuracy of 94.3%.

In their contribution, Abd El-Rahiem and Hammad [52] presented a multi-fusion ECG authentication system based on internal deep fusion algorithm. Transfer learning technique is used to extract the deep features of ECG signals in this system. After that, they used SVM as a separate classifier for authentication and reported final authentication accuracy of 99.4%. Finally, AlDuwaile and Islam [53] employed CNN and a single heartbeat to develop an ECG recognition system.

They reported accuracy of 99.90%, 98.20%, and 94.18% for different databases. Unlike most of the enumerated DLMs, our proposed approach is built on an end-to-end structure that eliminates the need for different machine learning stages while recording better accuracy. Details of this proposed model are presented in the next section.

MATERIALS AND METHODS

Structurally, our proposed CNN-based DLM (or simply CDM) combines the hitherto separate stages (i.e., preprocessing, feature extraction and classification) of conventional machine learning techniques into a compact unit. Like most of the studies highlighted in the previous section, ECG biometric data from the PTB database [54] was employed for all stages of this study. This dataset [54] comprises of ECG signals from 290 subjects, which are separately fed into our proposed CNN model.

Finally, the proposed model classifies the acquired ECG signal as an accepted or unaccepted (i.e., rejected) class. For example, in our earlier demonstration of vehicle access control systems based on ECG authentication in Fig. 2, the system grants access depending on the identification of the driver, i.e., whether he/she is accepted as an authorized driver or not. Fig. 3 presents a general outline depicting the integration of the DLM in the ECG authentication framework.

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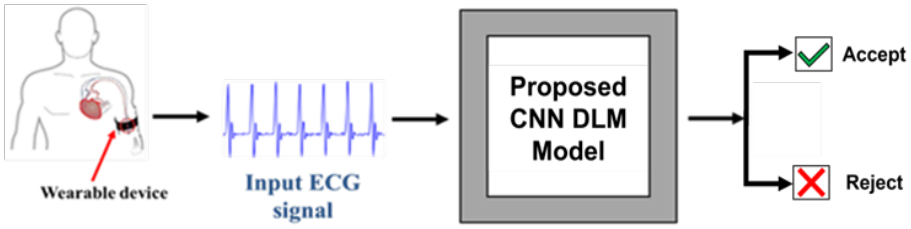


Fig. 3. Block diagram outlining implementation of the proposed model.

Dataset and Implementation Framework

Table 2. PTB classes

Class	Numberofsubjects
Myocardial infarction	148
Myocardial hypertrophy	7
Myocarditis	4
Heartfailure	18
Dysrhythmia	14
Bundlebranchblock	15
Valvular heart disease	6
Miscellaneous	4
Healthy	52

As mentioned earlier, the PTB dataset [54] is used throughout this study. This is a widely used multi- session dataset made up of 549 records from 290 subjects whose ages range from 17 to 87 years of which 28% were female and 72% were male.Each subject has signal duration of between 1 to 5 records. Each recording consists of 15 measured signals: 12 regular leads and 3 Frank ECG leads with a sampling frequency of 1,000 Hz. Thespecifications of the PTB recorder are as follows:

- ±16 mV as an input voltage with 16 input channels and 100 Ω input resistance
- 16-bit resolution with 0 to 1 kHz bandwidth.
- Maximum noise voltage of 10 μV (pp).
- The noise level recording during signal collection. Furthermore, the diagnostic classes of the subjects in the dataset are summarized in Table 2 [54].

Additionally, we used two-second Lead II ECG signals made up of 2,000 sample

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pulses in total. Finally, we normalized each record using Z-score normalization with standard deviation and mean set at 1 and 0, respectively.Results emanating from the implementation of our proposed model are compared alongside standard studies published in the literature as reported later in Section 4 and discussed in Section 5.

Proposed CNN-based Deep Learning Model

CNN has been credited for the remarkable success of DLMs. Since its debut for applications in pattern recognition and computer vision, it has been deployed in numerous fields, including biometrics, authentication, etc. Typically, a CNN consists of different layers: convolution, fully connected, and pooling. The convolution layer is used to extract features from the input that are fed into the pooling layer where some parameters may be reduced. Finally, the fully connected layer converts the features matrix to a vector and combined these features together to create a model.Fig. 4 depicts details of the CNN architecture for our proposed model comprising of five convolution processes that consist of three maxpooling, three dropout, two fully connected layers as well as a soft max layer that is employed in the authentication stage, whose output is the final decision, i.e., accept or reject.Probing further, we now note that in our model, each ECG record (with 2,000 samples) is fed to our network for training and testing. The proposed CNN model comprises of five 1D convolution layers that are actuated using a rectified linear unit (ReLU) activation function [54] and three max pooling layers that are followed by two fully connected layers and a soft max activation function, which is used to transform the outputs of the classifier into probabilities for each class of the two classes (i.e., accept or reject). In accomplishing this, the convolution operation is executed using (1).

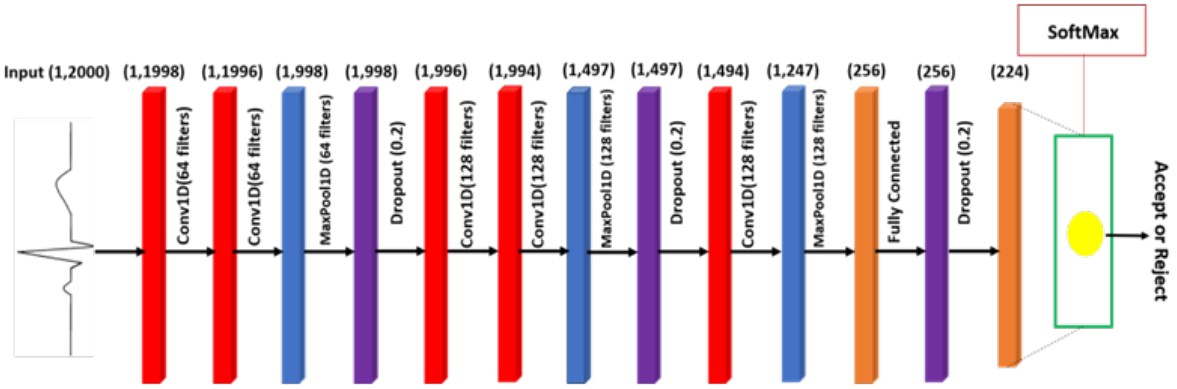


Fig. 4. CNN operation of the proposed model.

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$$Y_p = \sum_{k=0}^{N-1} x_k f(n-k)$$

Where N, x, and f are the element number, signal, and filter in the input signal (x), respectively and the vector y represents the output signal. We start with the 1D convolution layers with 64 filters whose size increases sequentially to 128 filters in the last layers (to extract more features from the input). The filter size is set at 3 with a step-wise stride. We also pool the output of every convolution layer output at a stride of 2. Further, a dropout with a 0.2 probability rate is used to prevent the network from over fitting [55] By ignoring some randomly selected neurons during the training. It is noteworthy that the dropout is important in large networks that have complex fitting but few labeled samples. In addition to serving as a classifier, the fully connected layer maps the dimensions, i.e., high to low, as presented in Table 3. For authentication, we employed the soft max function defined in (2) because it is differentiable, and it optimizes the cost function, and its outcome produces the final decision as presented in Fig. 3.

$$\sigma(\vec{Z})i = \frac{e^{Z_i}}{\sum_{j=1}^{k} e^{Z_j}}$$

WhereZi is the input vector to the softmax function, k is the number of classes and is normalization term.

Training

Table 3 Composition of Different Layers of Proposed Model

Layernumber	Layername	Sizeof filter	Stride	Numberofkernels	Sizeofoutput
1	Convolution	3	1	64	1998×64
2	Convolution	3	1	64	1996×64
3	Maxpooling	2	2		998×64
4	Dropout		Rate=0.2		998×64
5	Convolution	3	1	128	996×128
6	Convolution	3	1	128	994×128
7	Maxpooling	2	2		497×128
8	Dropout		Rate=0.2		497×128
9	Convolution	3	1	128	494×128
10	Maxpooling	2	2		247×128
11	Fullyconnected			512	256
12	Dropout		Rate=0.2		256
13	Fullyconnected			448	224
14	Softmax			2	2

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Stochastic gradient descent with momentum [56] is used for training our model with a batch size of 10 samples. Furthermore, hyper-parameters comprising of weight decay, learning rate and number of epochs were set at 0.00005, 0.0001 and 100, respectively. Subsequently, these parameters were adjusted iteratively to obtain optimum performance.

Testing

Testing was performed after each run of the training epoch on our model. We divided the data into three parts: 60% for training, 30% for validation, and 10% for testing. Additionally, a 5-fold cross-validation approach [57] is employed for training and testing sets during authentication. In this approach, the ECG data are randomly shuffled and divided into five equally-sized subsets.

After that, we ran five experiments where 90% of the data was reserved for training and validation and the remaining 10% for testing. Finally, we evaluated the final performance of the method by calculating the mean of all folds.

To ascertain the performance of our CNN model, we considered two factors: evaluating the impact of the proposed model using a 5-fold approach [57] and the authentication performance of the proposed method relative to established ECG authentication methods. Algorithm 1outlines the execution of the above procedure while Algorithm 2 summarizes steps for the execution of the CNN model.

Algorithm 1. Execution of proposed protocol

1:**Input**:Raw input data $x=x1,x2, \ldots,xn$;% with 2000 samples for each record

2:CNNx;%the input data are directly fed into the CNN network to retrieve the extracted feature vectors 3: $F=F1,F2,\ldots,Fn$;% the extracted feature vectors are mapped into high-dimensional space

4: **for** each ECG signal starting from i = 1 to the length of ECG signal (2000 samples)5: **extract** CNN features$F$;

6: **endfor**

7:Ftrain, Ftest,Ltrain,Ltest$F$,L;%split features and labels into train and test subsets

8: **Output**: F to SoftMax activation function; % transform the outputs of the classifier into probabilities for each output of the two classes (Accept or Reject)

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Algorithm2. Execution of proposed CNN model

Function CNN (x)

x set the input data.

Conv 1 RELU_Activation_Func (Conv1D)

Conv 2 RELU_Activation_Func (Conv1D)

Conv 2 Max_Pool1D (Conv 2)

Conv 2 Dropout (0.2)

Conv 3 RELU_ Activation_Func (Conv1D)

Conv 4 RELU_ Activation_Func (Conv1D) Conv 4 ☐ Max_Pool

Conv 4 Dropout (0.2)

Conv 5 RELU_ Activation_Func (Conv1D) Conv 5 ☐ Max_Pool

Fully connected Reshape (Conv 5) Fully connected ☐ Dropout (0.2)

Fully connected RELU_ Activation_Func (Fully connected)

Output Softmax_Func (Fully connected)

Return Output End Function

Experimental Validation

Our proposed model was executed on an Intel Core i7-6800K CPU with NVIDIA GTX 1080ti GPU and 16 GB RAM workstation equipped with MATLAB R2018a open-source Deep Learning toolbox. The training time of the CNN model was 0.5 hour while the prediction lasted 0.03 seconds.

Performance Metrics

For performance assessment, we employed standard metrics, such as accuracy (A), precision (P), recall (R), EER, receiver operating characteristic (ROC) curve and F1-score (F1) that depend on false positive (FP), false negative (FN), true positive (TP), and true negative (TN) rates as defined in the equation matrix in Fig. 5 [26] where N and M represent the number of sets applied in the 5-fold validation and the number of classes, respectively. We note that the ROC curve is a graph used to show the performance of a statistical model with two output classes (such as the Accept or Reject) outcome of our model. It provides a trade-off between specificity and sensitivity and classifiers with high accuracy tend to have curves closer to the left corner [58].

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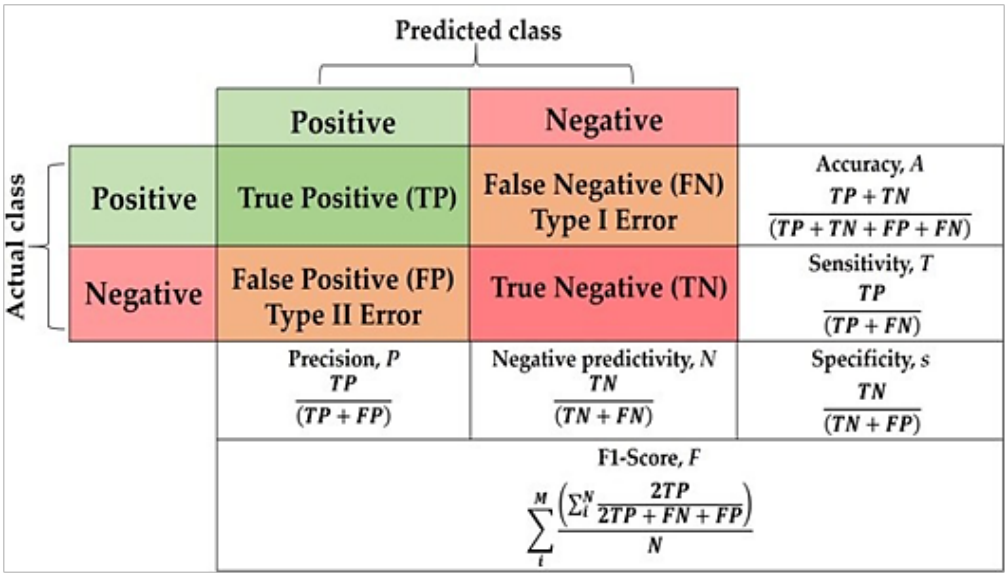


Fig. 5 Equation matrix for binary quality metrics. Adapted from [26].

Authentication Results

Table 4 Authentication results per fold on PTB database

Numberoffolds	Accuracy (%)	Precision (%)	Recall(%)	F1-score(%)
1	99.3	99.6	99.98	99.7
2	98.7	98.9	99.98	99.4
3	100	100	100	100
4	99.5	99.7	99.99	99.8
5	100	100	100	100

Using the performance metrics presented in Fig. 5, in this subsection an overview of the outcomes of the authentication process is presented and subsequently discussed in the next section. Table 4 presents the authentication results for the proposed system per fold for the PTB database by computing the accuracy, precision, recall and F1-score in each fold. Furthermore, these outcomes are presented as confusion Matrices for each fold in Fig. 6 from where an average accuracy of 99.50% is reported. Based on this figure, 99.4% of the genuine classifications are correctly verified (i.e., true positive) while a meager 0.04% of impostor cases are wrongly verified as genuine classifications, i.e., false positive classifications (or type II error).

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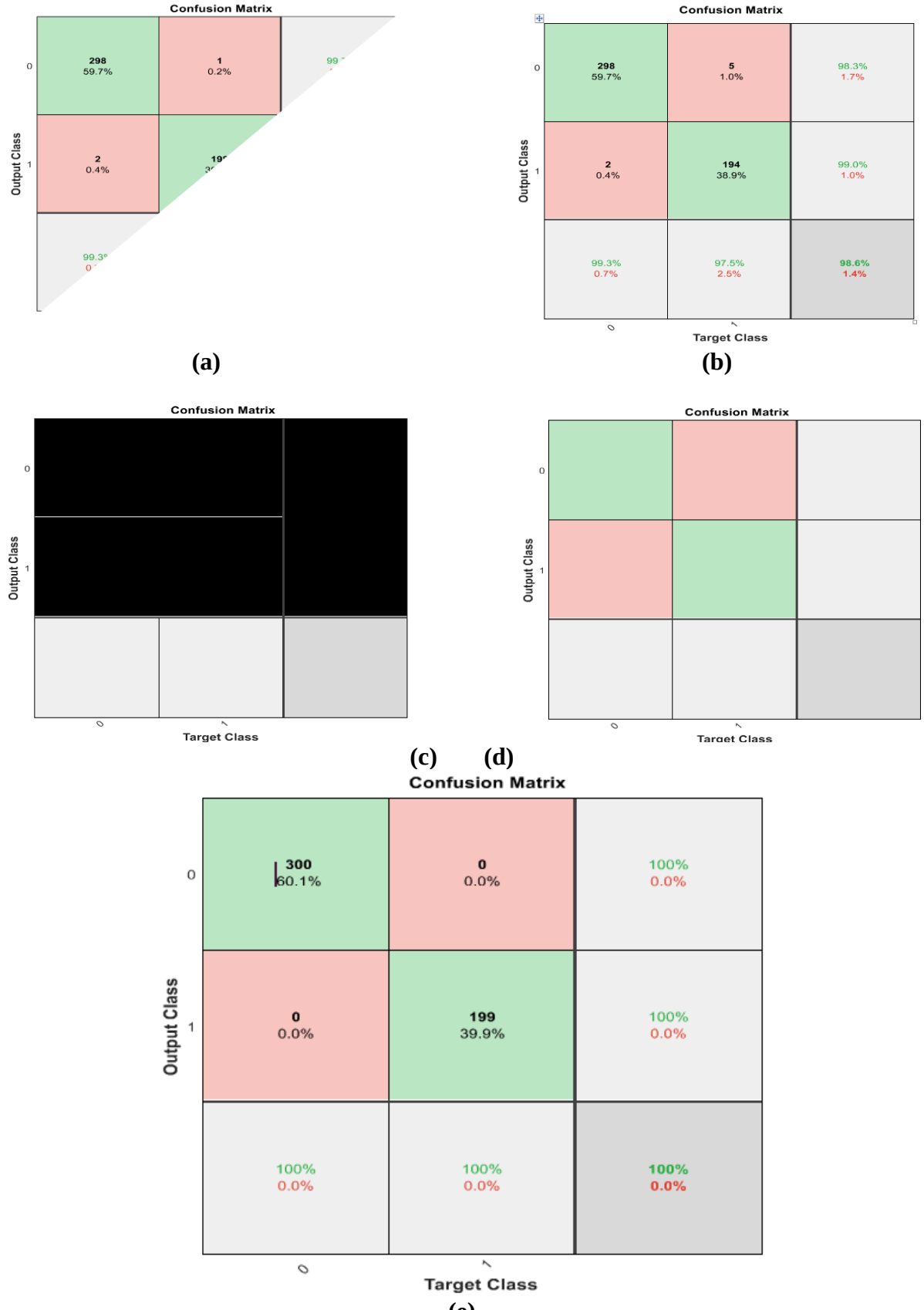


Fig. 6. Confusion matrix for each fold of proposed model: (a) 1-Fold, (b) 2-Fold,(c) 3-Fold, (d) 4-Fold, and (e) 5-Fold.

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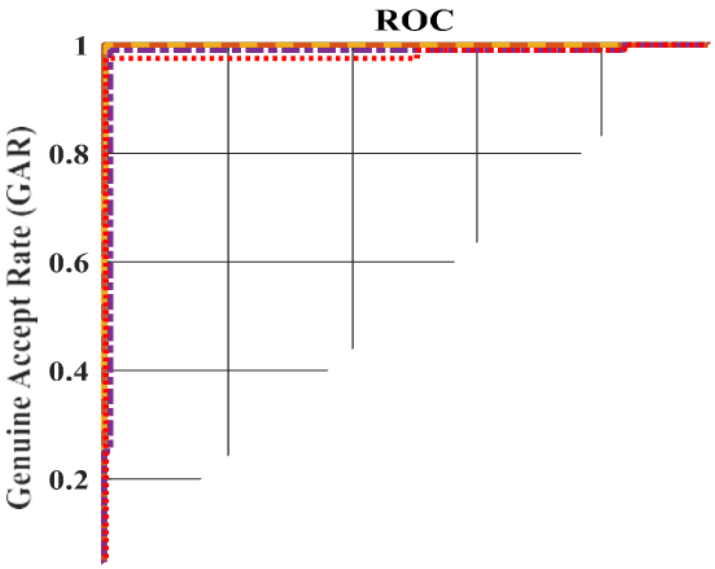


Fig. 7. ROC curves of each fold of proposed model.

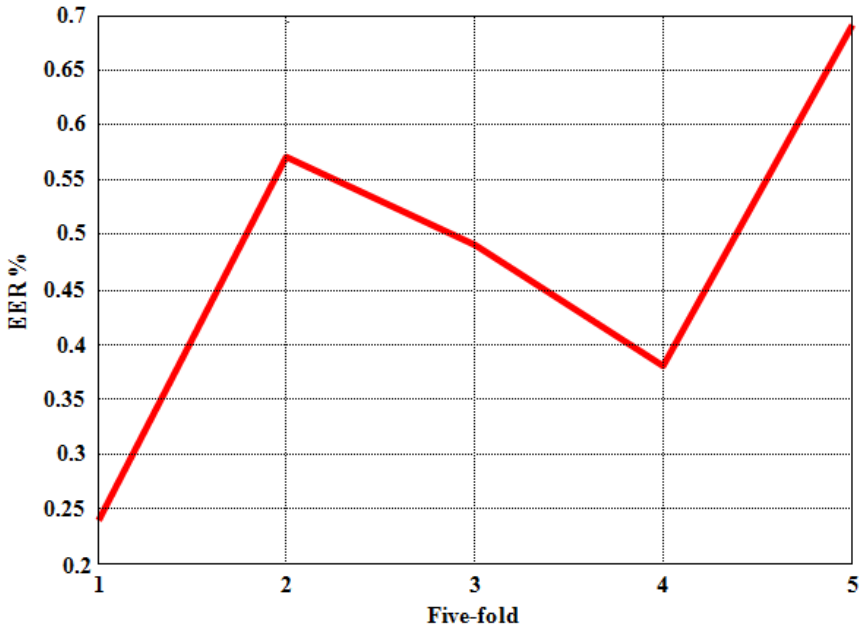


Fig. 8. Variation in EER (%) for different number of folds in proposed model

Additionally, Fig. 7 presents the ROC curves for the proposed CNN model in each fold, while the variation in the EER (computed as a percentage rate when FP=FR) for our proposed model during the 5- fold validation is presented in Fig. 8. Here, it is noteworthy that an average EER of 0.47% is reported for the proposed model, while, as presented in Fig. 9 (i.e., plots of accuracy and logarithmic loss), it can be deduced that the model converges after 50 training epochs. Consequently, this setting is adopted for the remaining experiments that are reported.

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Discussion of Results

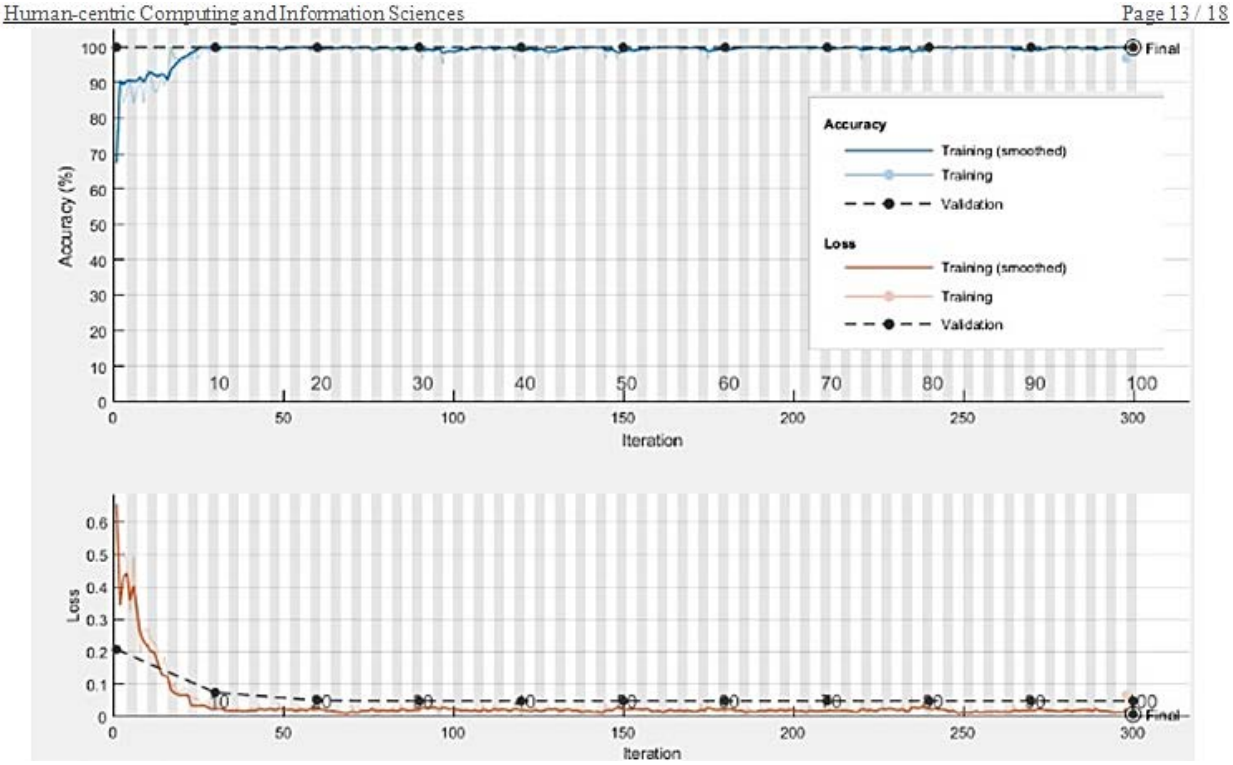


Fig9. Accuracy and loss curves for the proposed CNN technique.

Whereas analysis of the results presented earlier in Section 4 can provide deductions regarding the efficiency and robustness of the proposed authentication method, in this section we present an analysis of such outcomes. From the authentication results in Table 4 and the confusion matrices in Fig. 6, we can observe that the proposed method attained high accuracy in each fold (i.e., in some cases maximum accuracy of 100% was reported), which, as previously reviewed in Section 2, manifests the robustness of the proposed model and its capacity to overcome over fitting that is ascribed to CLM models,. Additionally, the ROC curves reported in Fig. 7 present evidence that the proposed model has high authentication in each fold as exhibited by the number of genuine acceptance rate relative to the number of false acceptance rate in each fold. Finally, the variations in EER reported in Fig. 8 support our claims regarding the accuracy of the proposed model since low EER is recorded in each fold.To undertake an effective performance analysis, the authentication performance obtained using the PTB database based on [13–16] and deep learning techniques [17–23] highlighted earlier in Section 2 (presented in Table 5), alongside outcomes from our proposed model. There from, we note the better

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performance (in bold) of out technique. Moreover, for a balanced discussion, we start by highlighting the key features of the methods used in the assessment (i.e., as presented in Table 5).Unlike the deep learning approaches mentioned in Table 5 [17–20, 23], our proposed approach is built on an end-to-end structure that eliminates the need for different machine learning stages. Furthermore, our system is less complex than other systems because only one ECG lead was used. Additionally, unlike the enormous size of the filters in the convolution layers (e.g., 5×1 and 8×1) employed by the model in [17], which increases the computational cost, our model utilizes a reasonable number of filters throughout the network (i.e., 3×1 filters). Moreover, unlike methods (such as [18, 20, 21]) that recorded low accuracy using noisy data, as an end-to-end structure, our model can manage such noisy signals. This eliminates the need for a preprocessing stage, and it works directly on the input ECG signal instead. Furthermore, unlike our proposed model, previous studies in [17–20, 22, 23] reported the use of separate classifiers, which exacerbates computational complexity and cost.As noted earlier in Section 3, the use of Fog computing servers to execute and evaluate the proposed deep learning model, provides access to radio networks to enhance computational and storage capabilities. Therefore, the overall performance of these systems is improved since computationally- intensive operations of the model are processed on the edge server. In this regard, Fog computing models are considered prominent solutions that can offer lower latency and high bandwidth to support their implementation in real-time applications.

We conclude our discussion by once again highlighting the contributions of our study vis-à-vis its merits as highlighted in the reported discussions in this section:

- As demonstrated throughout the study, our model is less complex than other authentication approaches because it is conceived and built as a completely end-to-end structure.
- This end-to-end structure supports direct application on the ECG signal, thus circumventing the need for any preprocessing stage. This facilitates dealing with noisy ECG signals.
- Finally, compared to previous DLMs, our proposed model exhibits better robustness and effectiveness in overcoming traditional drawbacks, such as over fitting.

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Table5. Comparison of different authentication algorithms based on PTB database (see text for further details)

ECG authentication framework	**Study**	**Methodology**	**Performance (EER, %)**
Machine learning methods	Louis et al. [13] Local binary patterns	Sequential sampling and bagging	
	Societal. [14]	Pulseactiveratio Euclideandistance	9.89(fornormalclass) 19.15(forabnormalclass)
	Gürkanetal. [15]	Autocorrelation/Discrete cosine transformMel-frequency cestrum co efficient Linear discriminant analysis Three-nearest-neighbor	2.84
	Hammad etal.[16]	Improved bio-hashing	32
		Matrix operation Feedforward neural network	14
Deeplearning models	Labatietal.[17]	CNN	2.90
	Hammadetal.[18]	Two-dimensionalCNN	3.20
	HammadandWang [19]	One-dimensionalCNN	3.50
	Hammad et al. [20]	Scanning and removing techniques CNN	1.63
	Hammad et al. [22]	CNN Residual CNN (ResNet)	1.53 (using CNN) 1.39 (usingResNet)
	Chu et al. [23]	Parallel multi-scale one-dimensional residual network	0.59
	Proposed	**1D convolutional neural network**	**0.47**

CONCLUSION

Our study advances previous machine and deep learning technique for ECG-based human authentication by leveraging the use of Fog computing servers that can be connected to IoT devices while maintaining access to computational andstorage resources. The proposed model

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employs a CNN- based DLM to realize an end-to-end structure that eliminates the need for any handcrafted preprocessing, feature extraction and classification, procedures that are known to impact on the computational complexity of the system. Consequently, our model exemplifies the potentials of integrating the edge-computing frameworks to enhance cost effectiveness and efficiency in terms of lower authentication time. Using the PTB ECG database outcomes of experiments reported support claims that the proposed method significantly outperforms existing classical machine and deep learningModels in terms of authentication EER. These outcomes indicate improved generalization and robustness for our proposed approach.

With appropriate modifications, some real-life applications of the proposed model, such as a car access control system, customer authentication for the banking system, and applications in many medical systems are interesting directions to implement the proposed study. Despite its potentials, however, some drawbacks of the proposed model include its lack of cancel ability, i.e., the ability to protect the ECG feature templates [59, 60]. Overcoming these shortcomings of the proposed model are among our short- term goals whereas, in the future, we intend to use template protection techniques to safeguard the system against spoof attacks and explore other applications for the model across other biometrics systems. Furthermore, we will assess security threats and propose mechanisms against attacks as well as applications in advanced IoT infrastructures [46].

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