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ResNet-Attention model for human authentication using ECG signals

Mohamed Hammad[1,2] | Paweł Pławiak[3,4] | Kuanquan Wang[1] | Udyavara Rajendra Acharya[5,6,7]

[1]School of Computer Science and Technology, Harbin Institute of Technology, Harbin, China

[2]Faculty of Computers and Information, Menoufia University, Menoufia, Egypt

[3]Department of Information and Communications Technology, Faculty of Computer Science and Telecommunications, Cracow University of Technology, Krakow, Poland

[4]Institute of Theoretical and Applied Informatics, Polish Academy of Sciences, Gliwice, Poland

[5]Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore, Singapore

[6]Department of Biomedical Engineering, School of Science and Technology, Singapore School of Social Sciences, Singapore, Singapore

[7]Department of Bioinformatics and Medical Engineering, Asia University, Taichung, Taiwan

Correspondence
Paweł Pławiak, Department of Information and Communications Technology, Faculty of Computer Science and Telecommunications, Cracow University of Technology, Warszawska 24 st., F-3, Krakow 31-155, Poland.
Email: plawiak@pk.edu.pl, plawiak@iitis.pl, plawiak.pawel@gmail.com

Abstract

Authentication is the process of verifying the claimed identity of the user. Recently, traditional authentication methods such as passwords, tokens, and so on are no longer used for authentication as they are more prone to theft and different types of violations. Therefore, new authentication approaches based on biometric modalities such as heartbeat pattern obtained from electrocardiogram (ECG) signals are considered. Unlike other biometrics, ECG provides the assurance that the person is alive, and is considered as one of the most accurate recent methods for authentication. In this article, *two* end-to-end deep neural network models for ECG-based authentication are proposed. In the first model, a convolutional neural network (CNN) is developed and in the second model, a residual convolutional neural network (ResNet) with attention mechanism called ResNet-Attention is designed for human authentication. We have used 2-s duration ECG signals obtained from two ECG databases (Physikalisch-Technische Bundesanstalt [PTB] and Check Your Bio-signals Here initiative [CYBHi]) for authentication. Our proposed ResNet-Attention algorithm achieved an accuracy of 98.85 and 99.27% using PTB and CYBHi, respectively. The results obtained by our developed model show that the performance is better than existing algorithms and can be used in real-time authentication systems after the validation with more diverse ECG data.

KEYWORDS

authentication, biometrics, convolutional neural network, DNN, ECG, end-to-end structure, ResNet

1 | INTRODUCTION

Conventional authentication methods, such as passwords, security tokens, identify cards, and other methods can be easily stolen and fabricated. Therefore, the mentioned methods are unable to meet the increasing requirements of personal information security (Matyáš & Říha, 2002). To solve this issue, researchers have developed biometrics-based authentication systems with higher recognition rate to replace the traditional authentication systems. Recently, many human authentication approaches are introduced, one of the most important of these methods is electrocardiogram (ECG), because, unlike the traditional biometric modalities, it provides the guarantee that the individual is alive. The ECG-based biometric has other advantages such as minimal computational requirement, lower template size, and so on (Sufi & Khalil, 2008; Sufi, Khalil, & Habib, 2010). These advantages make ECG very popular in many applications (Abdar et al., 2019; Amrani, Hammad, Jiang, Wang, & Amrani, 2018; Halifax, 2015; Hammad, 2019; Hammad, Ibrahim, & Hadhoud, 2016; Hammad, Maher, Wang, Jiang, & Amrani, 2018; Pławiak, 2018a; Pławiak, 2018b; Pławiak & Abdar, 2020; Pławiak & Acharya, 2019; Rajesh et al., 2019; Tuncer, Dogan, Pławiak, & Acharya, 2019; Yıldırım, Pławiak, Tan, & Acharya, 2018), such as customers authentication as in Halifax bank (Halifax, 2015). Halifax has shown the effectiveness of Nymi band (Nymi, 2016) instead of traditional authentication methods.

An ECG is a common medical test that records the electrical signals in the heart. A single cardiac cycle ECG trace comprises of *three* core waves—P-wave, T-wave, QRS-complex, and five core intervals—PR-interval and segment, QT-interval, and ST-interval and segment. The P-wave and QRS occur when the atria and ventricle are, respectively, depolarized, whereas the T-wave occurs when the ventricles are repolarized (Fischer & Ritter, 2012). The PR-interval is extending from the onset of the P-wave to the initial point of the Q-wave. While the QT-interval covers the range from the start of the QRS-complex to T-wave's end point. The final interval, the ST-interval covers from S-wave terminal point to T-wave ending point. We have two segments, the PR-segment and ST-segments. The former is the time between the termination marks of the P-wave to the start mark of the Q-wave, while the latter range between S-wave's termination point to the starting of the T-wave. The previous discussion shows that the ECG signals can be used as a biometric. The ECG is universal, as it is conditional on the heart activity, which occurs in every living individual. It is unique, as its characteristic is different from individual to other.

The focus of previous studies on ECG-based authentication has been broadly in two areas (Table 5): (a) conventional machine learning techniques (Bin Safie, Nurfazira, Azavitra, Soraghan, & Petropoulakis, 2014; Choudhary & Manikandan, 2015; Gurkan, Guz, & Yarman, 2013; Guven, Gürkan, & Guz, 2018; Hammad, Luo, & Wang, 2019; Karegar, Fallah, & Rashidi, 2017; Louis, Komeili, & Hatzinakos, 2016; Pal & Singh, 2018; Safie, Soraghan, & Petropoulakis, 2011; Salloum & Kuo, 2017) or (b) deep learning-based approaches (Hammad, Liu, & Wang, 2018; Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Luz, Moreira, Oliveira, Schwartz, & Menotti, 2018; Labati, Munoz, Piuri, Sassi, & Scotti, 2018).

Nowadays, machine learning is becoming popular and effective tool to solve problems in the field of medicine (Abdar & Makarenkov, 2019; Jaworek-Korjakowska & Tadeusiewicz, 2014; Książek, Abdar, Acharya, & Pławiak, 2019; Szaleniec et al., 2013; Szaleniec, Tadeusiewicz, & Witko, 2008; Tadeusiewicz, 2015). It has been used for human authentication (Omara, Emam, Hammad, & Zuo, 2017; Omara, Li, Xiao, Adil, & Zuo, 2018; Topcu & Erdogan, 2019), especially using ECG (Bin Safie et al., 2014; Choudhary & Manikandan, 2015; Gurkan et al., 2013; Guven et al., 2018; Hammad, Luo, & Wang, 2019; Karegar et al., 2017; Louis et al., 2016; Pal & Singh, 2018; Safie et al., 2011; Salloum & Kuo, 2017). The major short comings of these methods (Bin Safie et al., 2014; Choudhary & Manikandan, 2015; Gurkan et al., 2013; Guven et al., 2018; Hammad, Luo, & Wang, 2019; Karegar et al., 2017; Louis et al., 2016; Pal & Singh, 2018; Safie et al., 2011; Salloum & Kuo, 2017) are given below:

- Used small number of ECG data and hence, these methods may not perform well on larger dataset.
- Utilizing very complex algorithms and costly in terms of authentication time.
- Model is developed using one database.
- Obtain low-performance authentication when working on other databases, which leads to overfitting.
- Require designing of feature extractor and classifier.

Therefore, to overcome the shortcomings present in the machine learning approaches, we are proposing a novel deep learning approach for human authentication using ECG signals.

Recently, deep neural network (DNN) was applied on several studies to construct biometrics-based authentication systems (Alotaibi & Mahmood, 2016; Jung & Heo, 2018; Marra, Poggi, Sansone, & Verdoliva, 2018; Nogueira, Lotufo, & Machado, 2017; Rehman, Man, & Liu, 2018). However, few previous authentication systems based on convolutional neural network (CNN) and residual convolutional neural network (ResNet) are developed using ECG signals (Hammad, Liu, & Wang, 2018; Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Luz et al., 2018; Labati et al., 2018).

Most of previous studies based on deep learning approaches are time-consuming and computationally intensive as they used preprocessing and segmentation techniques (Hammad, Liu, & Wang, 2018; Luz et al., 2018; Labati et al., 2018) and QRS detection (Labati et al., 2018). Also, all these studies have used a separate classifier for authentication, which will make these methods more complex. Also, these methods (Hammad, Liu, & Wang, 2018; Labati et al., 2018) are sensitive to the ECG signal quality and may not perform well in the presence of noise. Moreover, in Luz et al. (2018) and Labati et al. (2018), working on multiple lead ECG recordings, will make the method more complex. Finally, most of these studies have used big convolution filters, which increase overall the cost as in Luz et al. (2018) and Labati et al. (2018).

The main novel contribution of this article is summarized below:

1. We propose a new efficient DNN model for human authentication based on ECG to achieve high performance as compared to the previous authentication systems.
2. This is the first method to develop an end-to-end CNN without requiring any handcrafted preprocessing, feature extraction and classification stages. Hence, it reduces the computing cost and makes our method less complex than other previous methods.
3. Use of ResNet model without requiring any machine learning stages is the novelty of this work.
4. We have fed the ECG signal without any preprocessing to the CNN and ResNet model. Hence, our models are more robust to noise.

2 | MATERIALS AND METHODS

This study proposes two novel DNN models with an end-to-end structure for human authentication based using ECG signals. Our methods combine all stages of machine learning approaches such as preprocessing, feature extraction, and classification instead of developing a different model for each of these stages. The individual ECG signal from the database is directly fed into the proposed DNN models. Then, our proposed models decided if this person can access the system (Accept) or not (Reject) as shown in Figure 1.

2.1 | ECG data sets

Most ECG authentication methods were tested using signals from the well-known ECG data sets: Physikalisch-Technische Bundesanstalt (PTB; Bousseljot, Kreiseler, & Schnabel, 1995), the Check Your Bio-signals Here initiative (CYBHi; Da Silva, Lourenco, Fred, Raposo, & Aires-De-Sousa, 2014), and MIT-BIH (Goldberger et al., 2000). However, the MIT-BIH is not suitable for biometric authentication because it is a single session dataset. So, in this study we have used the other databases (PTB and CYBHi database). The advantage of using PTB and CYBHi database is that, we can compare the results of the proposed method with the results obtained from the existing approaches in the literature. The details of the two databases are given below:

I. PTB database (Bousseljot et al., 1995)

- It made up of 549 records from 290 subjects (One to five records per subject).
- The age range of the subjects from 17 to 87 years (little less than two-thirds of the subjects were male and the remainder female).
- There are 15 measured signals in each record: 12 using traditional leads and the remaining 3 using Frank lead ECG signals.
- The sampling frequency of the signal is maintained at 1,000 Hz.

Throughout, we used lead II ECGs of 2-s duration selected from the PTB database (2,000 sample pulses). Then, each record is normalized using standardized Z-score normalization (each one has standard deviation = 1 and mean = 0). Figure 2 shows lead II ECG signals from this database.

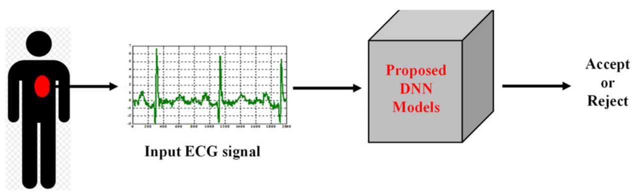

FIGURE 1 Overview of our authentication method

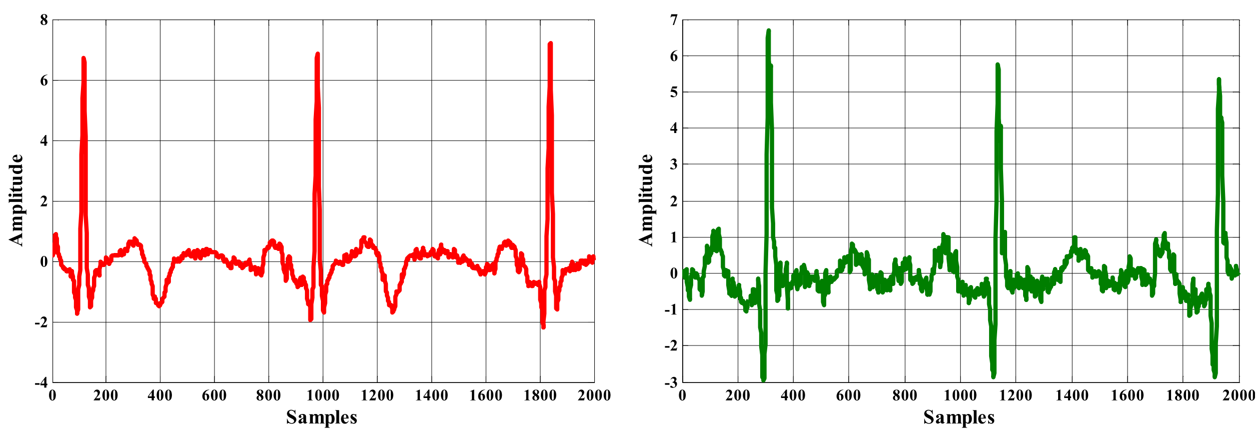

FIGURE 2 Typical ECG signals from PTB database. ECG, electrocardiogram; PTB, Physikalisch-Technische Bundesanstalt

II. CYBHi database (da Silva et al., 2014)

- The data comprise of 65 volunteers of which 49 are males and 16 are females, with an average age ranging from 21 to 41 years. Within 3 months, the number of subjects that recorded in two-sessions are 63.
- The data are collected using two ECG sensors. The first sensor collects the data with two dry electrodes and the second one collects the data with Electrolycras. These sensors were set on palms and the two fingers (the index and the middle).
- The sampling frequency of the signal is maintained at 1,000 Hz.

In this study, one lead ECG signals (2,000 sample pulses) of 2-s duration acquired with Electrolycras sensor from all subjects. In Electrolycras, the electrodes placed at the subjects' fingers are used to capture the ECG signals like a standard one ECG lead configuration. To make it easy and more comfortable for the subjects, they have used only two points, the positive poles, the negative, and a virtual ground circuit, unlike the standard leads (Silva et al., 2011). The database is normalized using Z-score normalization. Figure 3 shows the typical ECG signals from this database.

2.2 | The proposed end-to-end structure CNN model

This study deploys an end-to-end CNN model without requiring any handcrafted preprocessing, feature extraction and classification stages. To obtain the best performance of the proposed model, we compared the authentication performance of *five* CNN network structures with different layers (Table 1) as shown in Figure 4. The details of *five* network structures are shown in Table 1 and to ensure the integrity of the data, we employed the same filter size and padding strategy in each convolutional layer. Figure 4 shows that the performance can be obtained using Architecture 5 which consists of four convolution layers, two maxpooling layers, three dropout layers, and two fully connected layers.

The selected architecture from the proposed CNN models is shown in Figure 5. All the ECG signals (with 2,000 samples) are directly input to the proposed network for authentication. The signals pass-through *four* convolutional and *two* maxpooling layers followed by *two* fully connected layers and *one* softmax layer. All layers are provided with the rectified linear unit (ReLU) activation function that has shown outstanding performance for CNN training to introduce nonlinearity in the model. The pooling operation selects the maximum pooling strategy, which can achieve both dimensionality reduction and invariance. The size and stride of the pooled layer are 2×1 and 2, respectively. Further, to reduce the risk of

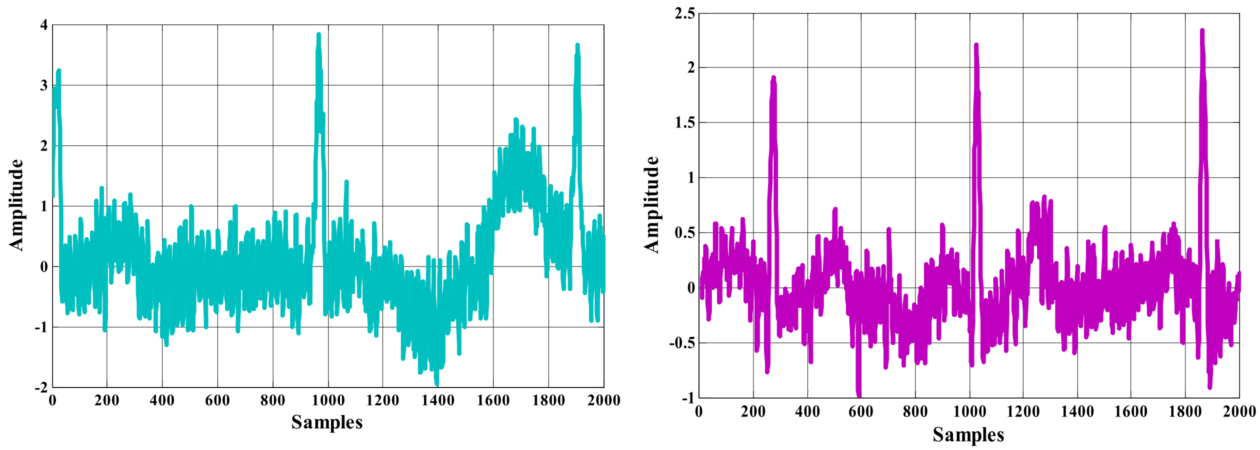

FIGURE 3 Typical ECG signals from CYBHi database. CYBHi, Check Your Bio-signals Here initiative; ECG, electrocardiogram

TABLE 1 Proposed *five* CNN architectures (the best architecture is in bold)

Architectures	Layers type
Arch 1	Conv-Conv-Max-Drop-Conv-Max-Drop-Fully-Drop-Fully-SoftMax
Arch 2	Conv-Max-Drop-Fully-Drop-Fully-SoftMax
Arch 3	Conv-Max-Drop-Conv-Max-Drop-Fully-Drop-Fully-SoftMax
Arch 4	Conv-Conv-Max-Drop-Fully-Drop-Fully-SoftMax
Arch 5	**Conv-Conv-Max-Drop-Conv-Conv-Max-Drop-Fully-Drop-Fully-SoftMax**

Abbreviations: CNN, convolutional neural network; Drop, dropout; Fully, fully connected; Conv, convolution; Max, max pooling.

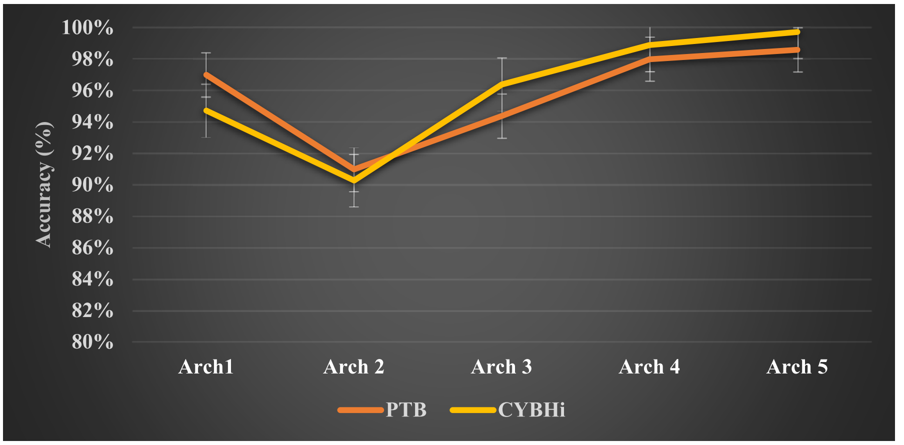

FIGURE 4 Comparison of performance of different CNN architectures using two databases. CNN, convolutional neural network

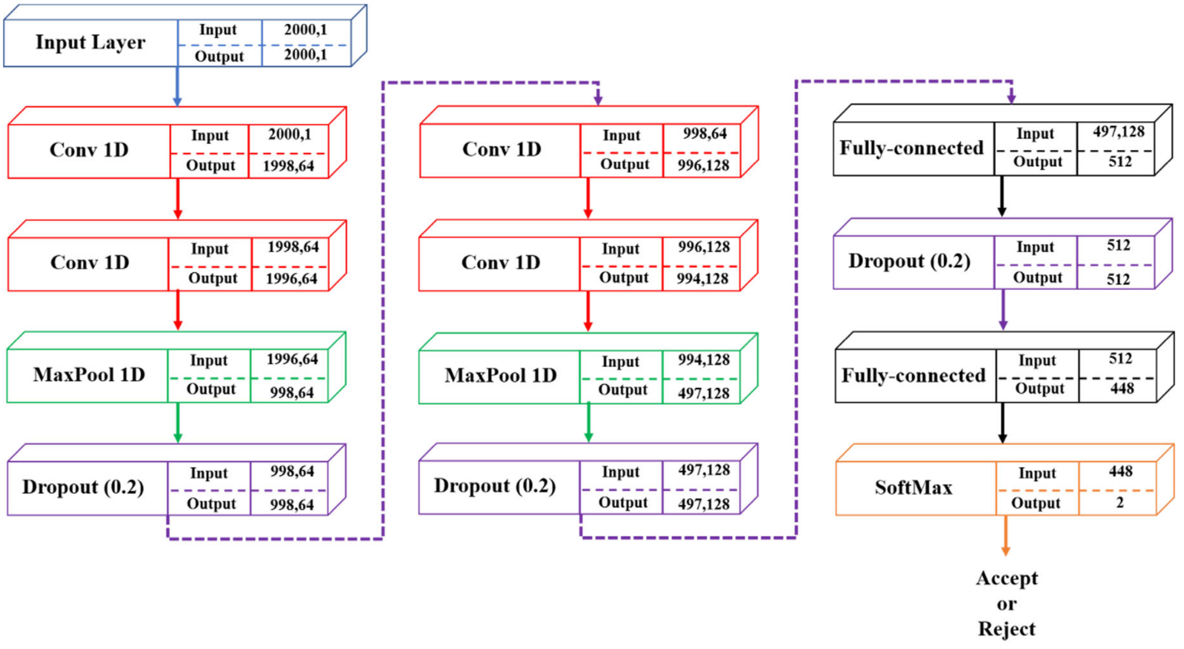

FIGURE 5 The proposed CNN model. CNN, convolutional neural network

TABLE 2 Details of various layers of the proposed CNN model

Layer Num	Type	Filter size	Stride	# of kernel	Output shape
Layer 1	Conv 1D	3 × 1	1	64	1,998 × 64
Layer 2	Conv 1D	3 × 1	1	64	1,996 × 64
Layer 3	MaxPool 1D	2 × 1	2	–	998 × 64
Layer 4	Dropout	–	Rate = 0.2	–	998 × 64
Layer 5	Conv 1D	3 × 1	1	128	996 × 128
Layer 6	Conv 1D	3 × 1	1	128	994 × 128
Layer 7	Maxpool 1D	2 × 1	2	–	497 × 128
Layer 8	Dropout	–	Rate = 0.2	–	497 × 128
Layer 9	Fully	–	–	512	512
Layer 10	Dropout	–	Rate = 0.2	–	512
Layer 11	Fully	–	–	448	448
Layer 12	SoftMax	–	–	2	2

Abbreviations: CNN, convolutional neural network.

encountering overfitting, dropout technique (Srivastava, Hinton, Krizhevsky, Sutskever, & Salakhutdinov, 2014) is used, and the dropout probability is set to .2. The fully connected layer acts as a classifier throughout the network structure while mapping high dimensions to low dimensions. Table 2 shows the details of various layers of the proposed CNN network.

2.3 | The proposed end-to-end structure ResNet model

The convolutional operation in a CNN model can effectively extract morphological features from a raw noisy 1D or 2D data (Kiranyaz et al., 2019). In the improved version of CNN, residual convolutional neural network (ResNet) overcomes the degradation problem in DNNs by adding shortcut links between its layers (Liu et al., 2019). Therefore, we employed ResNet for human authentication using raw ECG waveform. However, it is not effective and efficient to extract the features from ECG recording by only ResNet because the morphological features of ECG recordings are complex and hard to characterize. Hence, we used ResNet to extract the local features from raw ECGs and summarized the local-feature series by other network components such as attention mechanism. The network consists of *three* parts: local and global features learning parts followed by authentication part, as shown in Figure 6.

The local features are learned from input ECG signals using the local features learning part. Its output implemented by ResNet is called feature map which consists of sequence of local-feature vectors. This part consists of few initial layers and a main body which is made up of repeating substructures. Each substructure of the main body consists of a max pooling layer and a residual module. The pool size of the max pooling layer is 2, thus the length of the feature map is halved through each of substructures. And the number of substructures in a model depends on the input length. The longer input signal usually needs more pooling layers to compress the feature map to a certain length. Each residual module contains *two* convolutional layers, each of which consists of *three* layers: one layer for batch normalization (BN), one ReLU activation layer and one layer for dropout. The input of a residual module, through a shortcut connection is merged by summation with the output of second convolutional layer. As required by the merge operation, feature maps are padded before input into each convolutional layer to ensure that, the output length is equal to the input length. In the first convolutional layer, we used the kernel size of 32, and through each of four substructures, the kernel size is reduced by half until it is not more than 2. The local features learning part ends with BN and ReLU activation layer. Then the feature maps are input into the global features learning part, which summarizes the local features into a global feature vector which is used for the authentication.

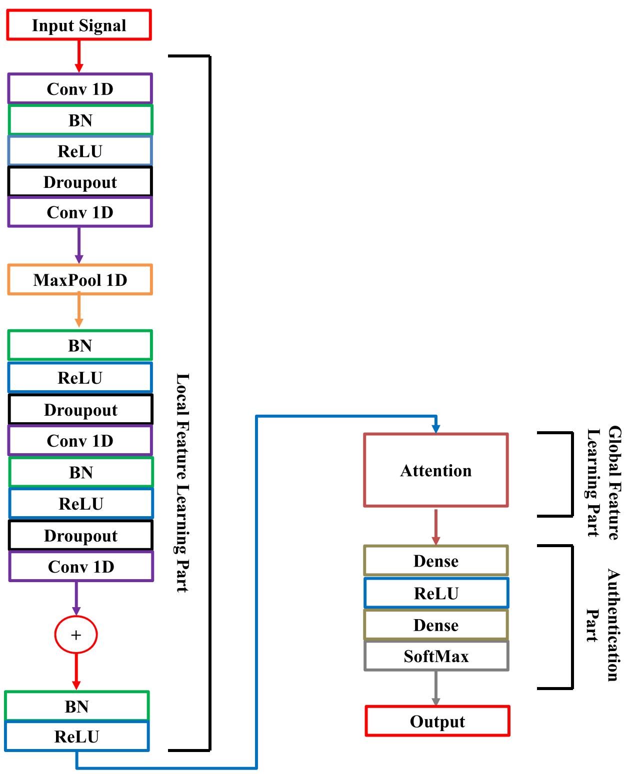

FIGURE 6 The architecture of the proposed ResNet-Attention

2.4 | Training

We used stochastic gradient descent with momentum (Krizhevsky, Sutskever, & Hinton, 2012) for training the proposed models with 10 samples for batch size. The hyper-parameters are set as follows: weight decay of 5×10^{-4}, learning rate of 10^{-3}, and number of epochs are set to 100. We changed these parameters iteratively until best performance is reached.

2.5 | Testing

The test is performed on our models after the completion of every training epoch. We separated the original data into *three* parts: 70, 20, and 10% for training, validation and testing part, respectively. We used the validation data for parameter tuning. While the data for testing are never seen by the classifier during training phase. Additionally, the 10-fold cross-validation approach (Duda, Hart, & Stork, 2001) is employed.

In order to verify the performance of our models, we worked on two aspects, evaluating the impacts of five architectures using 10-fold cross-validation approach (using the CNN model) and evaluating the performance of ResNet-Attention approach as end-to-end model. The authentication performance of the best architecture is compared with the existing ECG authentication methods. The proposed methods were tested on two databases (PTB and CYBHi database).

2.6 | Experimental setup

Our models were executed on a PC workstation with 3.30-GHz CPU, 32GB RAM, and the GPU is NVIDIA GeForce GTX 1080. All the algorithms are implemented using MATLAB R2017a software and we used deep learning toolbox, which is an open source MATLAB toolbox for deep learning. Based on this, 10-fold cross-validation approach was executed, and the mean authentication performance is reported. The training phase took about an hour and the predictions for each signal took about 0.02 s.

2.7 | Results

2.7.1 | Evaluation metrics

We have used accuracy (Accu), precision (Pr), recall (Re), F1-score (F1), and equal error rate (EER), which are related to false positive (FPr), false negative (FNr), true positive (TPr), and true negative (TNr) rates to evaluate the performance. These parameters are defined below:

$$\mathrm{Accuracy}(\mathrm{Accu}) = \frac{\mathrm{TPr} + \mathrm{TNr}}{\mathrm{TPr} + \mathrm{TNr} + \mathrm{FPr} + FNr}. \quad (1)$$

$$\mathrm{Precision}(\mathrm{Pr}) = \frac{\mathrm{TPr}}{\mathrm{TPr} + \mathrm{FPr}}. \quad (2)$$

$$\mathrm{Recall}(\mathrm{Re}) = \frac{\mathrm{TPr}}{\mathrm{TPr} + \mathrm{FNr}}. \quad (3)$$

$$F1_{\mathrm{score}}(F1) = 2 \times \frac{\mathrm{Pr} \times \mathrm{Re}}{\mathrm{Pr} + \mathrm{Re}}. \quad (4)$$

The equal error rate (EER) is the error value when the false rejection rate and the false acceptance rate are equal.

2.7.2 | Authentication results

End-to-end CNN network

Table 3 shows the mean ± *SD* for 10-fold with our proposed CNN method using two databases. It can be noted from the table that, Architecture 5 obtained best values (mean) with CYBHi and PTB databases as compared to other architectures. Architecture 4 obtained the best results (*SD*) as compared to other architectures using PTB database and achieved the second-best results with both databases.

TABLE 3 Summary of performances (mean ± *SD*) obtained for five models using the two databases with 10-fold strategy (best results are in bold)

Database	Architecture number	Accu	Pr	Re	F1
PTB database	Arch 1	0.969 ± 0.009	0.983 ± 0.006	0.966 ± 0.010	0.974 ± 0.007
	Arch 2	0.909 ± 0.011	0.934 ± 0.006	0.915 ± **0.005**	0.923 ± **0.005**
	Arch 3	0.943 ± **0.005**	0.959 ± 0.008	0.946 ± 0.010	0.953 ± 0.008
	Arch 4	0.979 ± 0.007	0.987 ± 0.005	0.980 ± **0.005**	0.985 ± **0.005**
	Arch 5	**0.985** ± 0.009	**0.993 ± 0.004**	**0.983** ± 0.008	**0.988 ± 0.005**
CYBHi databse	Arch 1	0.947 ± 0.010	0.970 ± 0.005	0.950 ± 0.008	0.960 ± 0.006
	Arch 2	0.902 ± 0.007	0.936 ± 0.009	0.916 ± 0.006	0.926 ± 0.007
	Arch 3	0.963 ± 0.005	0.978 ± 0.010	0.966 ± 0.005	0.972 ± 0.006
	Arch 4	0.988 ± 0.005	0.995 ± 0.004	0.987 ± 0.007	0.991 ± 0.005
	Arch 5	**0.997 ± 0.004**	**1 ± 0**	**0.995 ± 0.004**	**0.997 ± 0**

Abbreviations: CYBHi, Check Your Bio-signals Here initiative; PTB, Physikalisch-Technische Bundesanstalt.

TABLE 4 Confusion matrix for the two databases

Database	True/predicted	Genuine	Impostors	Accu (%)	Pr (%)	Re (%)	F1 (%)
PTB	Genuine	295	5	98.59	99.32	98.33	98.82
	Impostors	2	197				
CYBHi	Genuine	239	1	99.72	100	99.50	99.79
	Impostors	0	120				

Note: The variation in the EER (%) for the proposed CNN system through 10-fold for the two databases is shown in Figure 7.
Abbreviations: CNN, convolutional neural network; CYBHi, Check Your Bio-signals Here initiative; EER, equal error rate; PTB, Physikalisch-Technische Bundesanstalt.

TABLE 5 Performance of the proposed ResNet using two databases

Data set	Accu (%)	Pr (%)	Re (%)	F1 (%)
PTB	98.8	99.7	98.8	99.2
CYBHi	99.2	99.6	99.4	99.4

Abbreviations: CYBHi, Check Your Bio-signals Here initiative; PTB, Physikalisch-Technische Bundesanstalt.

It can be noted from Table 3 that; we have obtained Architecture 5 as our proposed model and we have considered it for all comparisons in the article.

The confusion matrix (presented in Table 4) showing results obtained using the proposed CNN system using two databases. From the table we can see that an accuracy of 98.59 and 99.72% are achieved using PTB and CYBHi database, respectively. In the case of the PTB database, 98.5% of the genuine are correctly identified as genuine and 99% of the impostors are correctly identified as impostors. In the case of the CYBHi database, 99.7% of the genuine are correctly identified as genuine and all impostors are correctly identified as impostors.

It can be noted from this figure that, the average EER for the CNN system is 1.53% for PTB database and 0.27% for CYBHi database.

Figure 8 shows the validation performance plots of the proposed CNN architecture using two databases.

End-to-end ResNet-attention network

The performance of the proposed ResNet using two databases is shown in Table 5. Figure 9 shows the validation graph of the proposed ResNet using two databases.

The variation of EER (%) for various folds using two databases is shown in Figure 10.

3 | DISCUSSION

The results of the proposed algorithms shown in Figures 7–10 illustrate that our proposed algorithms performed better using both databases. Also, our methods performed better using CYBHi database than with PTB database.

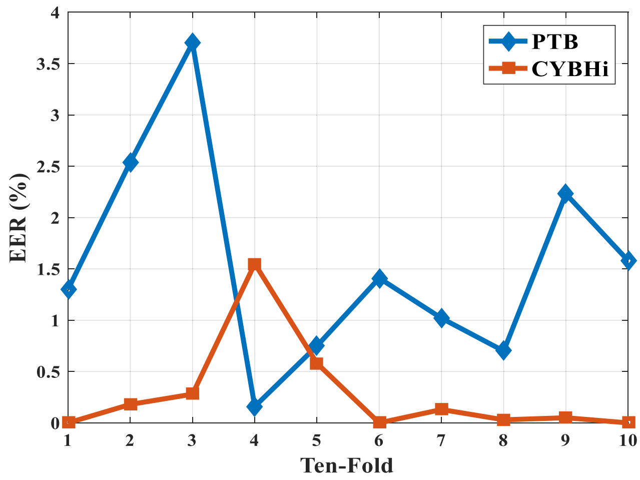

FIGURE 7 The variation EER (%) versus various folds for two databases. EER, equal error rate

The authentication performance obtained using two databases using machine and deep learning methods (Bin Safie et al., 2014; Choudhary & Manikandan, 2015; Gurkan et al., 2013; Guven et al., 2018; Hammad, Liu, & Wang, 2018; Hammad, Luo, & Wang, 2019; Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Luz et al., 2018; Karegar et al., 2017; Labati et al., 2018; Louis et al., 2016; Pal & Singh, 2018; Safie et al., 2011; Salloum & Kuo, 2017) are presented in Table 6.

It is evident from Table 6 that the proposed approaches are more robust and effective comparing to the other works. Few of previous works based on CNN have been used for ECG authentication (Hammad, Liu, & Wang, 2018; Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Luz et al., 2018; Labati et al., 2018). Labati et al. (2018) deployed deep CNN to extract the features of the ECG from more than a single lead and then compute the distance functions to compare them with the biometric templates. Their algorithm yielded 1.36% EER using PTB database for authentication. Luz et al. (2018) Introduced the use of convolutional networks to develop person recognition (verification) system using ECG. They generated the ECG features from 1-D CNN and 2-D CNN using two approaches: the raw ECG signal approach and the heartbeat spectrogram representation approach. After that, three fusion strategies (sum, mean, and multiplication rule) based on score level fusion are used. They reported an EER of 15.60% for 1-D CNN, 20.48% for 2-D CNN, and 13.93% for fusion of two CNN models. Hammad, Liu, and Wang (2018) presented a method that fused ECG with fingerprints using CNN for authentication. They worked on two-dimensional ECG signals and used one of the pretrained models (the VGG-Net model [Girshick, Donahue, Darrell, & Malik, 2014]) to extract the features. Then, they protected these features using the improved bio-hashing technique. Lastly, for authentication, they used Q-Gaussian multiclass support vector machine (QG-MSVM) classifier (Hammad & Wang, 2017). They obtained an EER = 3.2 using PTB database and EER = 2.9% for CYBHi database. Hammad and Wang (2019) also generated the feature template using the CNN model which they protected using the matrix operation technique. Finally, they proposed QG-MSVM classifier for authentication. They obtained an EER = 3.5% with PTB database. Hammad, Zhang, and Wang (2019) presented an authentication system using combination of manual features and CNN based on ECG. They used scanning and removing methods for feature extraction and CNN for classification. They achieved EER of 1.63 and 4.47% using PTB and CYBHi databases, respectively.

Except methods in Hammad, Liu, and Wang (2018), Hammad and Wang (2019), Hammad, Zhang, and Wang (2019), Luz et al. (2018), and Labati et al. (2018) of Table 6, rest all used external classifiers, preprocessing or feature extraction stages. Our algorithm is completely end-to-end structure without requiring any preprocessing, feature extraction, and classification stages. Furthermore, our systems are trained using only one ECG lead, which are less complex than other methods which used multi leads (Labati et al., 2018; Luz et al., 2018). Moreover, (Labati et al., 2018; Luz et al., 2018) in the first convolution layers, they worked on large filter size, which lead to higher computational cost while other methods (such as [Hammad, Liu, & Wang, 2018; Hammad, Zhang, & Wang, 2019]) provide poor sensitivity noise. This problem is solved using tolerable filters in all layers of the network. In Hammad, Liu, and Wang (2018) and Hammad, Zhang, and Wang (2019), authors used 2-D CNN, which is more complex with higher computational cost. Our proposed methods achieved better performance than the rest of the published works in Table 6.

The advantages of the proposed work are given below:

- Our systems are more robust and effective as compared to previous authentication systems developed based on deep learning technique (Hammad, Liu, & Wang, 2018; Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Labati et al., 2018; Luz et al., 2018).
- Our algorithms are completely end-to-end structure, which is less complex than other methods (Hammad, Liu, & Wang, 2018; Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Labati et al., 2018; Luz et al., 2018).
- Our models are insensitive to ECG signal quality (noise in ECG) unlike other previous methods (Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Labati et al., 2018; Luz et al., 2018).

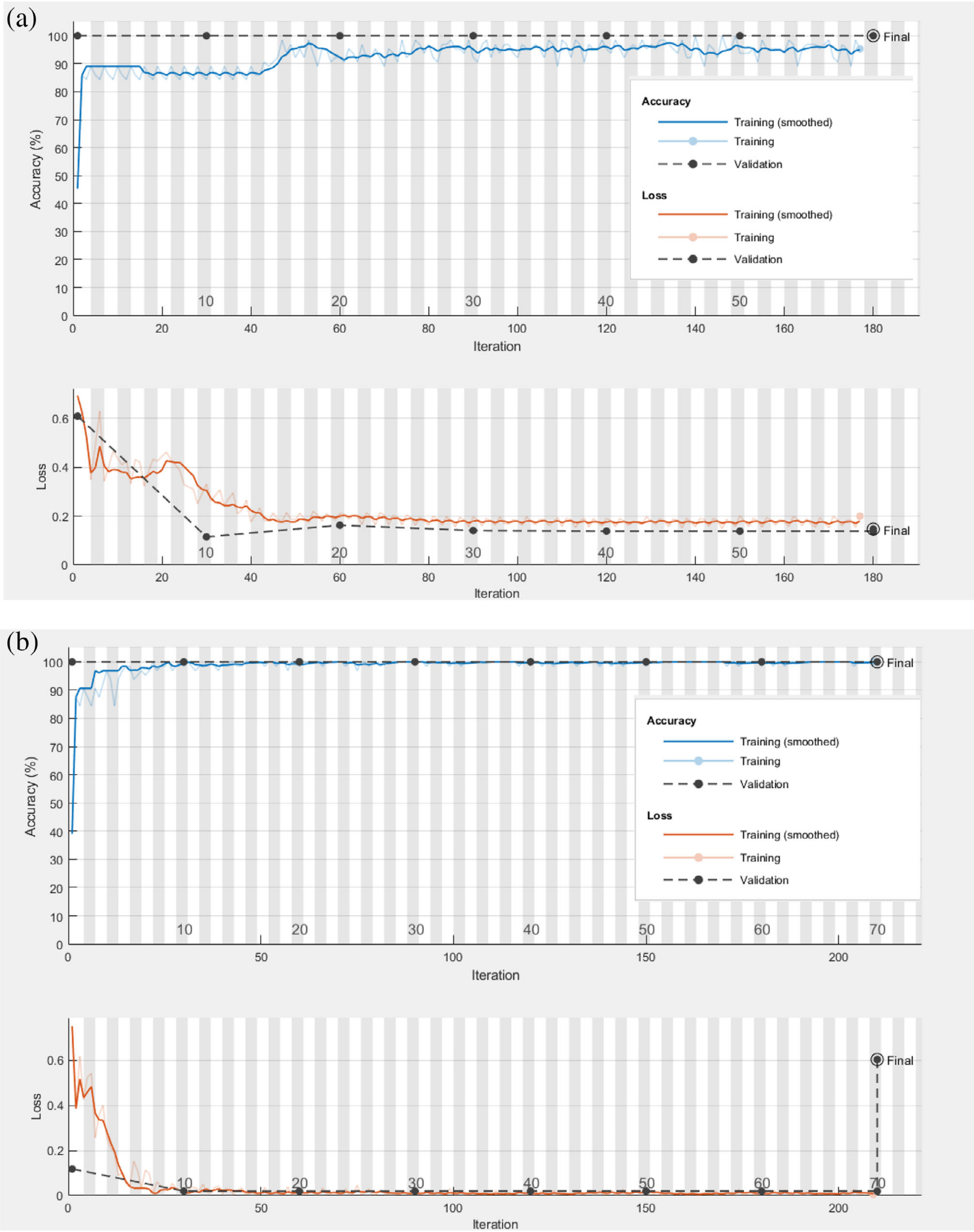

FIGURE 8 Snapshot of training and validation performances (accuracy [%] and loss) for the proposed CNN architecture obtained using two databases: (a) PTB and (b) CYBHi. CNN, convolutional neural network; CYBHi, Check Your Bio-signals Here initiative; PTB, Physikalisch-Technische Bundesanstalt

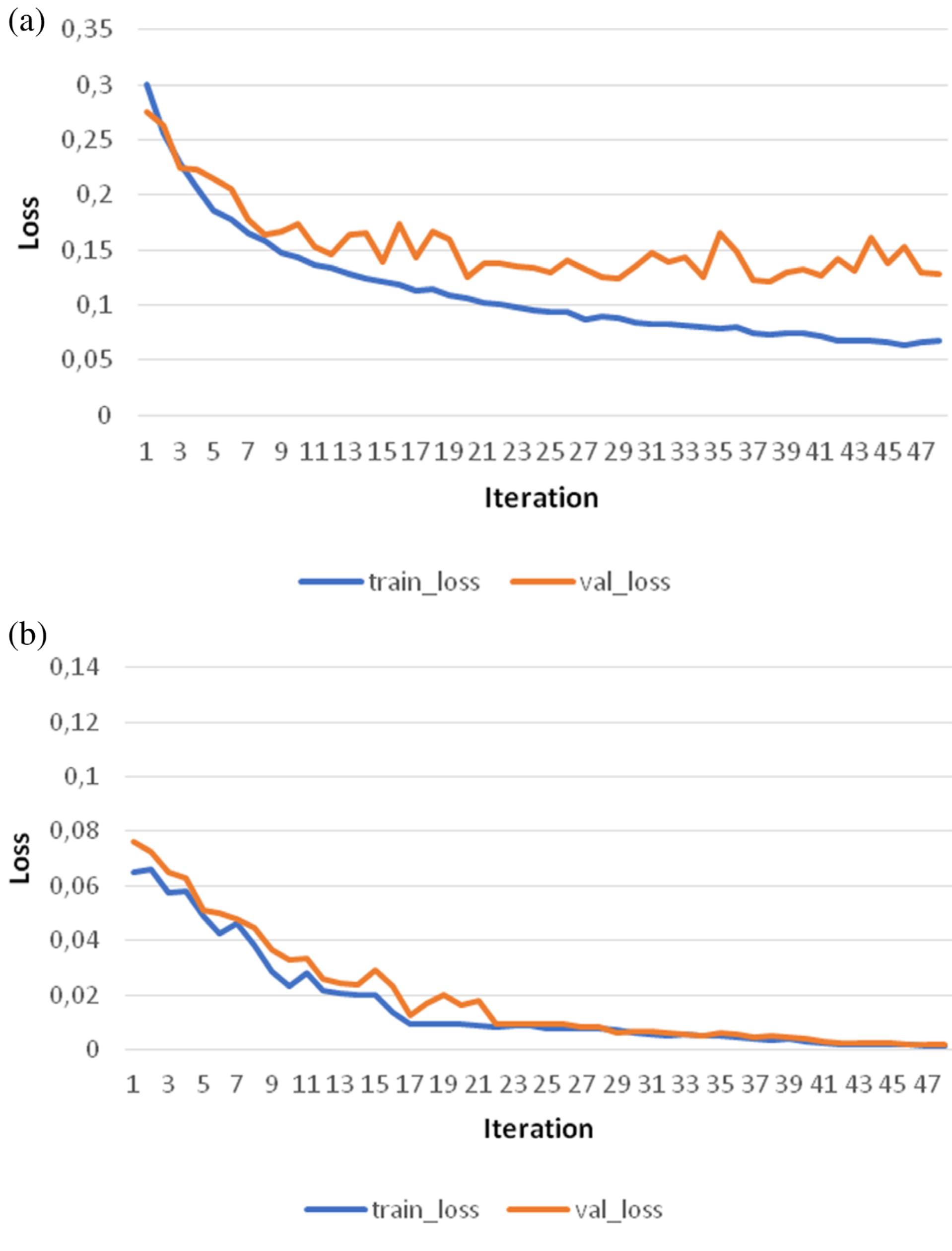

FIGURE 9 Training and testing losses versus different iterations for two databases. (a) PTB and (b) CYBHi. CYBHi, Check Your Bio-signals Here initiative; PTB, Physikalisch-Technische Bundesanstalt

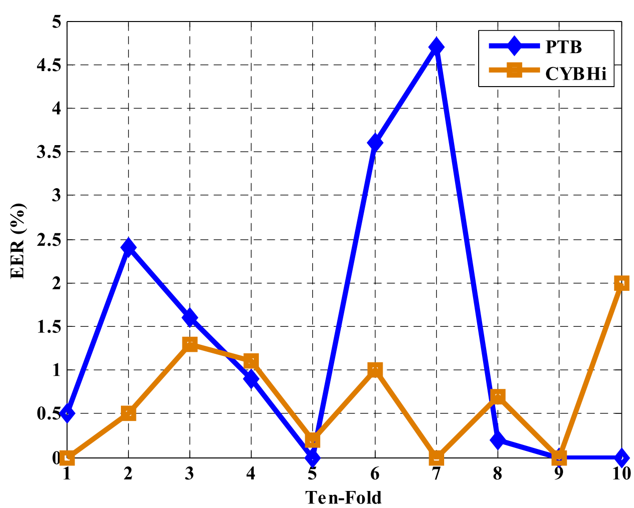

FIGURE 10 Plot of variation EER (%) versus various folds for two databases. The confusion matrix of results obtained using the proposed ResNet system using *two* databases is presented in Figure 11. It can be noted that, accuracy of 98.85 and 99.27% are achieved using PTB and CYBHi database, respectively. In case of using PTB database, 98.8% of genuine are correctly identified as genuine and 99% of impostors are correctly identified as impostors. In the case of the CYBHi database, 99.2% of genuine are correctly identified as genuine and 99.1% of impostors are correctly identified as impostors. CYBHi, Check Your Bio-signals Here initiative; EER, equal error rate; PTB, Physikalisch-Technische Bundesanstalt

FIGURE 11 Confusion matrices obtained using the proposed model for two databases. (a) PTB and (b) CYBHi. CYBHi, Check Your Bio-signals Here initiative; PTB, Physikalisch-Technische Bundesanstalt

The disadvantages of the proposed work are as follows:

- Requires large amount of data to achieve high accuracy.
- ECG template protection methods such as cancelable methods are not used.
- The first proposed system also used CNN deep learning structure like other works (Hammad, Liu, & Wang, 2018; Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Labati et al., 2018; Luz et al., 2018).

Differences with other systems are given below:

- We are the first to develop an end-to-end CNN and ResNet model without requiring any handcrafted preprocessing, feature extraction and classification stages unlike all other algorithms (Hammad, Liu, & Wang, 2018; Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Labati et al., 2018; Luz et al., 2018).

TABLE 6 Summary of automated authentication algorithms developed using ECG signals

	Author	Database	Approach	EER (%)	Disadvantages
Machine learning methods	Louis et al. (2016)	UofTDB (private data) PTB	1DMRLBP LBP Sequential sampling Bagging	UofTDB EER: 7.89% PTB EER: 10.10%	Cost-complexity Lower performance for multiple sessions' databases
	Pal and Singh (2018)	100 Records of PTB	FIR Haar wavelet Euclidean distance	EER: 2.88%	Used small number of ECG data Cost-complexity Time-consuming
	Safie et al. (2011)	112 PTB subjects	Pulse active ratio Euclidean distance	Healthy EER: 9.89% Arrhythmia EER: 19.15%	Sensitive to the ECG signal quality Time-consuming Used small number of ECG data
	Gurkan et al. (2013)	30 Subjects from PTB	AC/DCT MFCC LDA 3-NN	EER: 2.84%	Used small number of ECG data Cost-complexity
	Choudhary and Manikandan (2015)	MIT-BIH	GDF NCC DCT	EER: 8.70%	Cost-complexity Used single session database, small number of ECG data, and fixed threshold
	Bin Safie et al. (2014)	112 PTB subjects	PAT Euclidean distance	Healthy EER: 15.38% Arrhythmia EER: 23.88%	Sensitive to the ECG signal quality Used small number of ECG data
	Karegar et al. (2017)	18 Subjects of MIT-BIH	GHE HFD DFA RSA RQA SVM	EER: 4.88%	Used small number of ECG data Cost-complexity Used single session database
	Salloum and Kuo (2017)	ECG-ID MIT-BIH	RNN LSTM GRU	EER: 3.50%	Used single session database Cost-complexity
	Guven et al. (2018)	Fingertip ECG database (private data)	AC/DCT MFCC DFT LDA 5-NN	EER: 2.54%	Focused on identification Cost-complexity
	Hammad et al. (2019)	PTB MIT-BIH CYBHi	Improved bio-hashing and matrix operation FFNN	PTB EER: 32% EER: 14% MIT-BIH EER: 34% EER: 6% CYBHi EER: 17% EER: 9%	Cost-complexity Time-consuming Used fixed thresholds Focus on template protection
Deep learning methods	Labati et al. (2018)	PTB	CNN	EER: 2.90%	Cost-complexity Time-consuming Used on multiple leads No template protection Used large number of the data Sensitive to the ECG signal quality
	Luz et al. (2018)	CYBHi	1-D CNN 2-D CNN	1D EER: 15.60% 2D EER: 20.48%	Used large amount of data Cost-complexity Time-consuming No template protection

(Continues)

TABLE 6 (Continued)

Author	Database	Approach	EER (%)	Disadvantages
Hammad, Liu et al. (2018)	PTB CYBHi	2-D CNN	PTB EER: 3.2% CYBHi EER: 2.90%	Time-consuming Used large amount of data, separate classifier Cost-complexity
Hammad, Zhang et al. (2019)	PTB	1-D CNN	EER: 3.50%	Time-consuming Used large amount of data Used separate classifier Sensitive to the ECG signal quality
Hammad et al. (2019)	PTB CYBHi	Removing and scanning techniques CNN	PTB EER: 1.63% CYBHi EER: 4.47%	A few ECG records were analyzed Sensitive to the ECG signal quality
Proposed	PTB CYBHi	ResNet-Attention	PTB EER: 1.39% CYBHi EER: 0.68%	No template protection Used large amount of data
Proposed	PTB CYBHi	1-D CNN	PTB EER: 1.53% CYBHi EER: 0.27%	No template protection Used large amount of data

Abbreviations: CYBHi, Check Your Bio-signals Here initiative; ECG, electrocardiogram; EER, equal error rate; PTB, Physikalisch-Technische Bundesanstalt.

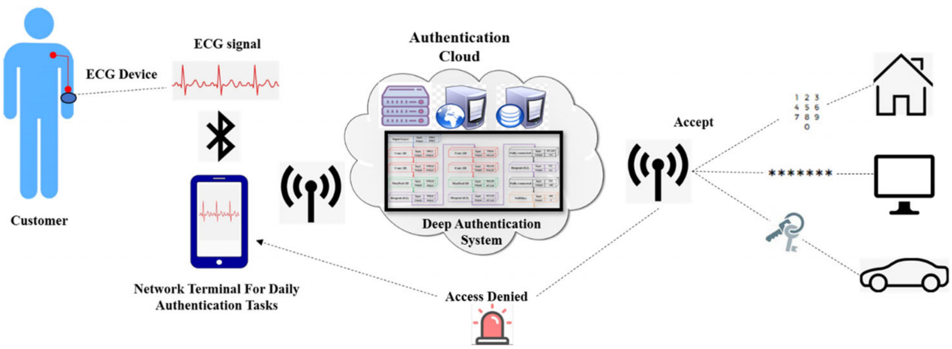

FIGURE 12 Illustration of deep authentication system using IoT. IoT, internet of things

- Our systems are trained using only one ECG lead signal unlike most of previous algorithms (Labati et al., 2018; Luz et al., 2018).
- Unlike most of previous deep learning approaches (Labati et al., 2018; Luz et al., 2018), we employed small filter size in the first convolution layers, which lead to lower computation cost and reduce noise effect.
- Unlike all previous methods, CNN is used for classification and we did not use separate classifier (Hammad, Liu, & Wang, 2018; Hammad & Wang, 2019; Hammad, Zhang, & Wang, 2019; Labati et al., 2018; Luz et al., 2018).

The proposed model can be deployed in the cloud using internet of things (IoT) as shown in Figure 12. The customer ECG signal is acquired using wearable sensors such as the Nymi Band (Nymi, 2016), the miBEAT (Ribeiro, Cardoso, & Andre, 2018), etc. This ECG signal is sent through Bluetooth of device (e.g., Mobile) for authentication task to the cloud where the proposed trained deep authentication model is kept. Our model will decide if this customer has the permission to access the system (e.g., home system) or not. If the proposed model rejects the customer, it will send a message "Access Denied" to the terminal device with alarm. Hence, the system is always secure from unauthenticated people.

4 | CONCLUSION

This article proposes two novel DNN models (CNN and ResNet-Attention) using ECG signals for human authentication. The signals are authenticated via an end-to-end structure without any handcrafted preprocessing, feature extraction and classification, which reduce the computational complexity of both systems. Unlike the previous authentication methods, the proposed systems use the original ECG signals without employing any signal filtering.

In this study, 2-s ECG signals obtained from two well-known ECG databases (PTB and CYBHi) are used for evaluation. The proposed CNN algorithm achieved an accuracy of 98.59 and 99.72% using PTB and CYBHi, respectively. The proposed ResNet-Attention algorithm achieved an accuracy of 98.85 and 99.27% using PTB and CYBHi, respectively. Our results confirm that the proposed algorithms better than the existing algorithms. Our proposed systems have a strong generalization ability and robust. In future, we intend to use template protection methods to increase the security of the system against spoof attacks. Also, we intend to apply the proposed model in other biometrics systems such as fingerprint, iris, and retina.

CONFLICT OF INTEREST

None.

ORCID

Paweł Pławiak https://orcid.org/0000-0002-4317-2801

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AUTHOR BIOGRAPHIES

Mohamed Hammad received his M.Sc degree in 2015, Information Technology Department, Faculty of Computers and Information, Menoufia University, Egypt and the Ph.D. degree in 2019, School of Computer Science and Technology, Harbin Institute of Technology, Harbin, China. He is currently an Assistant Professor in Faculty of Computersand Information, Menoufia University, Egypt. His research interests include Computer Vision, Machine Learning, Pattern Recognition, and Biometrics. Furthermore, he has been reviewing more than 100 papers for many International Journals such as IEEE Trans on Sys, Man and Cyber: Systems, IEEE Access, PLOSONE, Pattern Recognition Letters, Comp in Bio and Med, etc.

Paweł Pławiak, B.Eng., M.Sc., Ph.D., D.Sc. was born in Ostrowiec, Poland, in 1984. He obtained his B.Eng. and M.Sc. degree in Electronics and Telecommunications and his Ph.D. degree with honors in Biocyberneticsand Biomedical Engineering at the AGH University of Science and Technology, Cracow, Poland, in 2012 and 2016, respectively. He obtained his D.Sc. degree (habilitation) in Computer Science at The Silesian TechnicalUniversity, Gliwice, Poland, in 2020. He is the Head of the Department of Information and Communications Technology and an Associate Professor in Cracow University of Technology, Cracow, and Institute of Theoretical and Applied Informatics, Polish Academy of Sciences, Gliwice Poland. He has published morethan 20 papers in refereed international SCI-IF journals. He is a reviewer of many prestigious and reputed journals. His research interests include machine learning and computational intelligence (e.g., artificialneural networks, genetic algorithms, fuzzy systems, support vector machines, k-nearest neighbors, and hybrid systems), ensemble learning, deep learning, evolutionary computation, classification, patternrecognition, signal processing and analysis, data analysis and data mining, sensor techniques, medicine, biocybernetics, and biomedical engineering.

Kuanquan Wang is a full professor and PhD supervisor with School of Computer Science and Technology, and the deputy director of Research Center of Perception and Computing at Harbin Institute of Technology. Also, he was anassociate dean of School of Computer Science and Technology, HIT at Harbin, and the dean of School of Computer Science and Technology, HIT at Weihai from 2011 to 2014. He is a senior member of IEEE, a senior member of China Computer Federation (CCF) and ACM, and a senior member of Chinese Society of Biomedical Engineering. His main research areas include Image Processing and Pattern Recognition, Biometrics, Biocomputing, Modeling and Simulation, Virtual Realityand Visualization. He has published over 300 papers and 6 books, got more than10 patents, and won a second prize of National Teaching Achievement.

Udyavara Rajendra Acharya, Ph.D., DEng. is a senior faculty member at Ngee Ann Polytechnic, Singapore. He is also (i) Adjunct Professor at Taylors University, Malaysia, (ii) Adjunct Faculty at Singapore Institute of Technology- University of Glasgow, Singapore, and (iii) Associate faculty at Singapore University of Social Sciences, Singapore. He received his Ph.D. from National Institute of Technology Karnataka (Surathkal, India) and DEng from Chiba University (Japan). He has published more than 400 papers, in refereed international SCIIF journals (345), international conference proceedings (42), books (17) with more than 25,000 citations in Google Scholar (with h-index of 83), and ResearchGate RG Score of 46.9. He is ranked in the top 1% of the Highly Cited Researchers (2016, 2017, 2018 and 2019) in Computer Science according to the Essential Science Indicators of Thomson. He has worked on various funded projects, with grants worth more than 4 million SGD. He has three patents and in the editorial board of many journals. He has served as guest editor for many journals. His major academic interests are in biomedical signal processing, biomedical imaging, data mining, visualization and biophysics for better healthcare design, delivery and therapy. Please visit https://scholar.google.com.sg/citations?user=8FjY99sAAAAJ&hl=en Google Scholar for more details.

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