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Heart Disease Classification Using One Dimensional Convolutional Neural Network

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Abstract: In a body sensor network, vital signs such as heart rate, temperature and activity can be continuously tracked by wearable computers and relayed by personal devices to the cloud infrastructure, for both real-time health management and long-term health statistics purposes. However, along with boosting smart health sensors and applications, there are also increasing Heart Disease Detection requirements, which indicates that the given ECG of a particular person is normal or abnormal (abnormality is like heart attack and arrhythmia(An arrhythmia is a problem with the rate or rhythm of your heartbeat.). Heart Disease Classification is a promising technology for automatic and accurate individual recognition, focusing on these challenges.

Keywords: ECG, wavelet transformation, convolutional neural network, blind signal processing, data representation.

I. INTRODUCTION

Body sensor networks are reshaping people's daily lives, especially in smart health applications. In a body sensor network, vital signs such as heart rate, temperature and activity can be continuously tracked by wearable computers and relayed by personal devices to the cloud infrastructure, for both real-time health management and long-term health statistics purposes. However, along with boosting smart health sensors and applications, there are also increasing security and privacy requirements, to enable confidential biomedicine solutions, protect sensitive patient data, etc. Biometric-based human identification is a promising technology for automatic and accurate individual recognition, focusing on these challenges. Leveraging the uniqueness and permanence to individuals, biometric characteristics are more reliable than traditional token-based and knowledge-based individual recognition methods, such as the identity card and the username/password pair which may be lost or stolen. Two major categories of biometrics have been widely studied, i.e., behavioural and physiological ones, typical examples of which include gait, voice, signature, fingerprint, retina and face. Among physiological biometrics, bio-potentials are emerging powerful modalities and playing a more and more important role in human identification, benefitting from a fast progress in ubiquitous wearable devices and advanced signal processing/ machine learning techniques. In this paper, we take special interest in the Electrocardiogram (ECG) bio-potential, which is of many attractive characteristics for human identification applications, including universal, easily measured, unique and permanent. Specifically, the sinus node in the heart modulated by both sympathetic and parasympathetic nerves repeatedly produces electrical impulses and triggers the heart rhythm. Then the unique electrical waves, i.e., the ECG signal, are spread throughout the body and can be easily acquired with the ECG electrodes, either contacting or non-contacting ones. These attractive signal characteristics and the unobtrusive measurement mechanism make the ECG biometric highly promising in terms of the human identification. Convolutional Neural Network (CNN), as one of the major deep learning algorithms, is now gaining tremendous attentions leveraging its powerfulness in automatically learning the intrinsic patterns from the data, which can both prevent time-consuming manual feature engineering and capture hidden intrinsic patterns more effectively. Inspired by biological process of the visual cortex, CNN consists of multiple layers, each of which owns a small neuron collection to process portions of the input image. These collections are tiled to introduce region overlap, and the process is repeated layer by layer to achieve a high level abstraction of the original image. Inspired by the observation that the ECG stream can be seen as a 1D-image, the project explore how to effectively apply the 1D-CNN to ECG biometric identification, to avoid heavy feature engineering efforts, and also let the CNN capture more hidden patterns from data and learn a high level abstraction. This paper propose a novel wavelet domain Multi-Resolution Convolutional Neural Network Approach (MCNN) for ECG biometric identification, which avoids data-dependent complicated heartbeat detection/ segmentation techniques and heavy manual feature engineering that are both time-consuming and of a limited generalization ability. Specifically, it allows for blind segmentation of both normal and abnormal ECG streams (i.e., system can randomly select an ECG segment for user identification purpose), provides a multi resolution data representation in the wavelet domain to achieve richer temporal and spectral characteristics, and leverages the self-learning ability of CNN to automatically adapt its internal parameters (i.e., features encoded in

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network parameters) to wavelet-domain raw data. For algorithm evaluation, a one-lead ECG configuration is chosen, considering it is more convenient than the multi lead ECG configuration in daily applications, and of course, it also poses more challenges to the identification algorithm. Moreover, to demonstrate the generalization ability of the proposed framework composed of blind segmentation, data representation enrichment, phase difference removal, parallel multi resolution feature self-learning and classification, eight diverse datasets are considered which include not only different electrode placement methods (chest and wrist) but also various heart health conditions (with and without cardiac abnormalities), which are much more challenging than other works.

II. System Overview

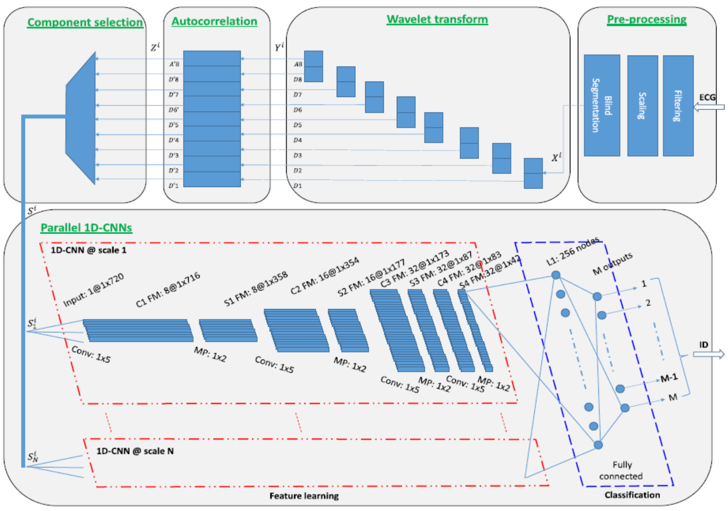

Fig.1 The system diagram of the proposed multi resolution convolutional neural network for human identification with blindly segmented ECG signal Notes. CNN: convolutional neural network; FM: feature map; Conv: convolution; MP: max pooling; C1 FM: convolutional layer 1 feature map; S1 FM: stage 1 final feature map; ID: identification; definitions of variables are given in the process. The system diagram of the proposed approach is shown in Figure 1, including pre-processing, wavelet transform, autocorrelation, component selection and parallel 1D-CNN. This section gives detailed description of our approach according to the signal processing. Specifically, the ECG stream is firstly blindly split up into signal segments with an equal length of two seconds without leveraging any heartbeat location information, which is not only immune to diverse morphological/beat-to-beat interval variability's, but also tolerant to signal artifacts that are usually major challenges in non-blind segmentation approaches. Afterwards, the ECG segments are transformed to the wavelet domain which is expected to reveal more detailed time and frequency characteristics in multiple resolutions than the original time domain. Then the auto-correlation operation is performed to each wavelet component to remove the blind-segmentation-induced phase difference. Finally, based on the enriched data representation, a 1D-CNN is applied to each wavelet component to learn the intrinsic patterns automatically, which allows for parallel feature self-learning in various wavelet scales, avoiding time consuming manual feature engineering. The learned features redirected by the CNN internal parameters are then used to identify users on the unseen random ECG segments.

Above process is divided into following parts
1. ECG Signal Preprocessing
2. Datasets
3. Wevlet Transform
4. Autocorrelation
5. Parallel 1-D CNN's

A. ECG Signal Preprocessing

The pre-processing operation includes three steps, i.e., filtering, scaling and blind-segmentation, as shown in Figure 1. Firstly, a 6-order Butterworth bandpass (2-50 Hz) filter is applied to each ECG recording to remove the baseline wander and the power line interference. Then all the recordings are scaled to be between 0 and 1 and subtracted by their mean to balance their contribution in the algorithm training phase, as (1-2) where ECG and ECGs are the original and the new ECG stream, respectively. Afterwards, the filtered ECG recording is blindly segmented to ECG windows Xi with an equal length where i is the window index. The window length is chosen as 2-second (720 samples) to include as least one heartbeat, since the typical range of heart rate is from 40 to 208 beats per minute.

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$$ECG^s = \frac{(ECG - \min(ECG))}{(\max(ECG) - \min(ECG))} \quad (1)$$

$$ECG^s = ECG^s - mean\left(ECG^s\right) \quad (2)$$

For each recording, 500 random windows are chosen, half of which are used to train the CNN (also component selection step in Fig. 1) and another half for testing. A example of randomly chosen ECG windows are shown in Figure 2, which usually include different number of heartbeats and highly different signal morphologies (either normal or abnormal). It is clear that the blind segmentation strategy can effectively avoid data-specific complicated heartbeat identification and segmentation techniques, but at the same time, also introduces a high variability to the ECG windows (number of heartbeats, onset of the segment, etc.) and poses a big challenge to the following data representation and machine learning algorithms. Automatic ECG classification is particularly useful for portable or wearable device and it is expected that few channel number (even single channel) would be found in these devices. And developed algorithm to handle small channel number of ECG. The timing of each heartbeat has been labelled for the corresponding R peak in the database. Hence, they can directly obtain the R-R intervals for each beat in segmentation. Nevertheless, numerous robust methods have already been available for R peak detection and algorithm for this is beyond the scope of current study.

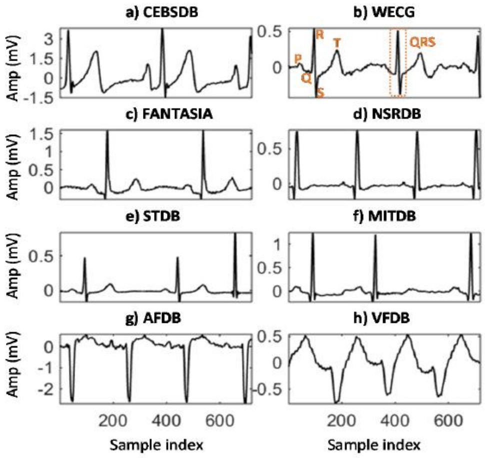

Fig.2 Blindly chosen ECG segments with diverse behaviors from eight normal and abnormal datasets. Amp: amplitude; P/Q/R/S/T: characteristic points of a normal heartbeat; QRS: central part of a heartbeat; definition of abbreviations is given in Table I.

B. Data Sets

TABLE I. Eight ECG Datasets

Abbreviations	# of subjects	Electrode placement	Type of abnormalities
CEBSDB	20	Lead I	Health
WECG	22	Lead I	Health
FANTASIA	40	Not specified	Health
NSRDB	18	Not specified	Quasi-health (no significant arrhythmias)
STDB	28	Not specified	ST depression/ elevation
MITDB	47	MLII (modified limb lead II)	Arrhythmia (along with 18 kinds of other diseases)
AFDB	23	Not specified	Atrial fibrillation
VFDB	22	Not specified	Malignant ventricular ectopy

Notes. CEBSDB: Combined measurement of ECG, breathing and seismocardiogram; WECG: Wrist-ECG measurement; NSRDB: MIT-BIH Normal Sinus Rhythm Database; STDB: MIT-BIH ST Database; MITDB: MIT-BIH Arrhythmia Database; AFDB: MIT-BIH Atrial Fibrillation Database; VFDB: MIT-BIH Malignant Ventricular Arrhythmia Database.

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Eight datasets with diverse ECG behaviors have been considered including CEBSDB, WECG, FANTASIA, NSRDB, STDB, MITDB, AFDB, VFDB as shown in Table I and Figure 2 These datasets may be acquired by different lead configurations.

Moreover, the first four datasets were collected from healthy or quasi-healthy participants, and last four include severe heart diseases such as ST depression/elevation, arrhythmia, atrial fibrillation and malignant ventricular ectopy. Considering these datasets were not acquired with the same sampling rate, all the ECG recordings were re-sampled to 360 Hz to fairly illustrate the performance.

C. Wavelet Transform

The wavelet transformation is expected to provide a richer data representation in the wavelet domain. Two examples of the transformed signals are given in Fig. 3 On the left part, the ECG signal is decomposed to eight details and one approximation. The detail 1 is extracted using the baby wavelet of the highest frequency, and the detail 8 is generated by the baby wavelet of the lowest frequency.

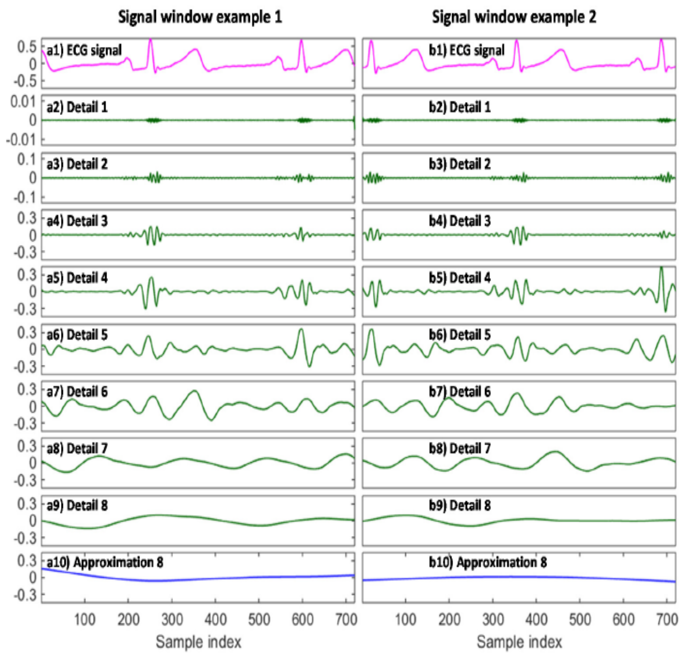

Fig.3 Multi-resolution representation of two signal segments in the wavelet domain.

As mentioned above, the wavelet transformation owns two advantages compared with STFT. Firstly, it overcomes the dilemma of resolution faced by STFT, i.e., a fixed small window results in a poor frequency resolution and a fixed large window causes a low temporal resolution. DWT, instead, applies windows of different sizes at different frequency levels. Specifically, a small window is chosen at a high frequency level to achieve a high temporal resolution such as detail 1, which is based on the consideration that high frequency component usually makes the signal quickly fluctuate and thus requires a high temporal resolution to track the signal dynamics. Moreover, a gradually extended window is applied to extract signal characteristics at a gradually decreasing frequency level. Take the detail 8 as an instance, the low frequency component makes the signal change slowly and thus a large window is applied to get a big picture of the signal in order to guarantee a high frequency resolution. In such a way, a time-frequency data representation of richer signal characteristics is obtained in the wavelet domain, taking into account different resolution requirements at different frequency levels.

D. Autocorrelation:

The autocorrelation operation is introduced to remove the phase difference due to blind segmentation. Fig. 4 shows similar outputs when applying auto-correlation to two wavelet domain signal segments given in Fig.3.

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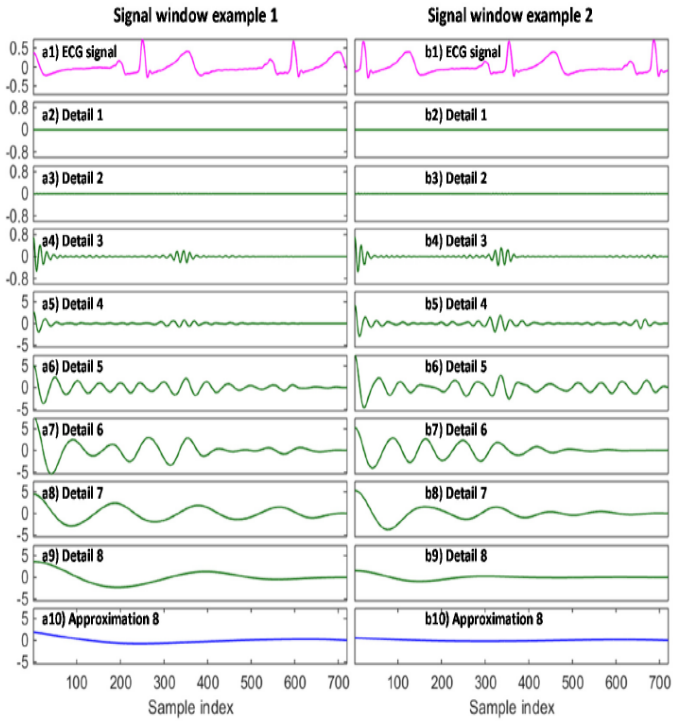

Fig.4 Phase different removal by auto-correlation to enable blind segmentation of ECG windows.

The auto-correlation calculates the correlation of a series with its delayed copy, i.e., the similarity between series as a function of the time lag between them. Therefore, it can effectively discover repeating patterns in the quasi-periodic ECG signals even with different numbers and occurrence time of heartbeats. After removing the phase difference, the multi resolution data can now be fed to the parallel 1D-CNN for automatic feature learning and user identification purpose.

E. CNN

There are several key considerations behind Convolutional Neural Network, such as local connections, shared weights, pooling operations and dropout techniques. As shown in Fig. 1, each CNN stage is composed of two types of layers, i.e., the convolutional and pooling layers. The convolutional layer includes many feature maps to extract a higher level representation from the previous layer. The connection between a unit and a local patch in the previous layer is called alter bank, which performs a discrete convolution operation. So the value of each unit is actually a local weighted sum of the previous patch, which is then fed into a non-linear activation function to determine whether this unit (neuron) fires or not. A same filter bank is shared by all units within a feature map, not only to form distinguishable local motifs from locally correlated values, but also to invariantly detect a same pattern even appearing in different locations. A widely used max pooling operation is chosen here, which captures the maximum of the corresponding local patch in the convolutional layer of the same stage. To further regularize the large number of parameters, the dropout technique is introduced which randomly ignores some neurons during training.
This operation can suppress the specialization of neighboring neurons which may result in a fragile model obverted to the training data (too smart in learning data), by forcing other neurons to step in and handle some more by their own (so they are also less dependent on the nodes they are connected to). In such a way, the network is more insensitive to the specific parameters of neurons (prevent neurons from co-adapting too much) and owns a better generalization ability to the unseen fresh data.

To train the multi-layer CNN, the back propagation approach is usually used, which computes the gradient of a predefined objective function with respect to all the neuron parameters by applying the chain rule for derivatives. The gradients can be propagated backwards from the output layer to the input layer, to adjust the parameters such that the network can converge to a state to be able to encode the training patterns. Leveraging key ideas in CNN architecture establishment and training techniques mentioned above, the neuron units are well organized in hierarchical features maps and can provide gradually increasing level of abstraction to enable the final identification task.

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III. Experimental Result and Discussion

In this section, detailed experimental results and discussion are given according to the signal processing flow as shown in Fig. 1.

1. Training Process result of ECG using CNN:

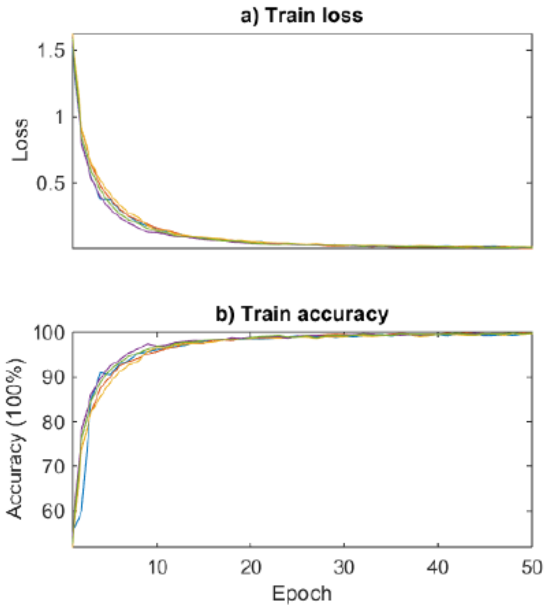

Fig.5 Training process of parallel 1D-CNN network C

The multi-scale 1D-CNN is firstly trained on the data with ground truth identify labels and then tested on the unseen fresh data. In the training phase, the network self-learns hierarchical features by convolutional and pooling operations from pairs of data representation and user label. An example of the training process is given in Fig. 5, where the top part shows the gradually decreasing training loss and the bottom part corresponds to the increasing training accuracy. The epoch size is set as 50 to balance under fitting and over fitting considerations. Actually, the network can already effectively learn most of the underlying patterns of the wavelet domain data and basically converges around 25 epochs. The learned hierarchical features encoded in the neuron connection parameters are then used to predict the user label on the testing data. The testing performance will be given later. It is worth noting that we have trained and tested the multi-scale 1D-CNN model on each dataset both for five times to average the performance, consideration that the learned hierarchical features are of some randomness resulting from the stochastic gradient descent optimization approach. Fig. 5 shows the training process for all five trials and interestingly we can and that they own a similar convergence speed. This is consistent with the theoretical study that poor local minima are rarely a problem in deep neural networks with a large number of parameters. Instead, the landscape of the object function is packed with a large amount of valleys which seems to mostly have local minima with similar values. Therefore, the randomness in SGD-based parameter tuning process actually often results in only small fluctuations to the convergence curve in the training process.

2. CNN topology selection result for Normal and abnormal person

The proposed MCNN algorithm is evaluated on eight ECG datasets. As mentioned above, the topologies of wavelet operation and neural network are determined based on the testing performance over the CEBSDB dataset, and are used on other datasets. The testing performance in terms of the confusion matrix of all eight datasets is given in and Fig. 6 and Fig. 7, and Corresponding identification rate is summarized in Table II.

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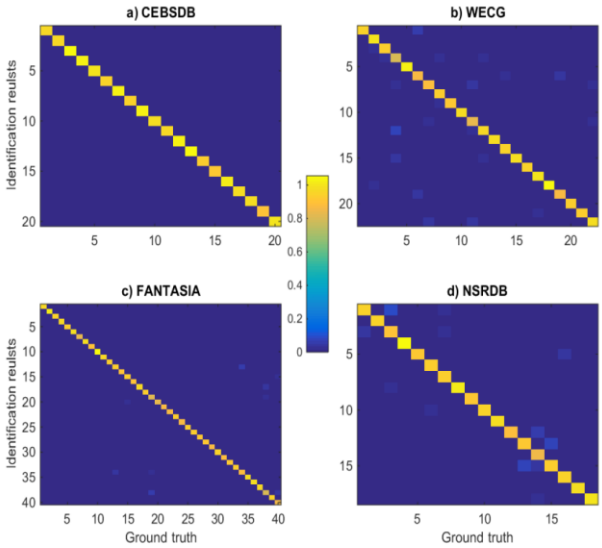

Fig.6 Confusion matrix for human identification based on testing data of four normal ECG datasets

TABLEII Identification rate of all datasets

Abbreviations	# Subject	Identification rate (%)
CEBSDB	20	99.0
WECG	22	94.5
FANTASIA	40	97.2
NSRDB	18	95.1
Averaged @ normal datasets	**25**	**96.5**
STDB	28	90.3
MITDB	47	91.1
AFDB	23	93.9
VFDB	22	86.6
Averaged @ abnormal datasets	**30**	**90.5**
Averaged @ all datasets	**28**	**93.5**

For four normal ECG datasets, the performance visualization in Fig. 6 clearly shows that the trained MCNN can effectively identify the human subjects (diagonal entries with a yellow color), with very little false positives or false negatives (non-zero off-diagonal entries). The top part of Table II also illustrates the high identification rate for these four normal ECG datasets, from 94.5% to 99.0%. It is worth noting that there is still a high identification rate even for the FANTASIA dataset with a number of subjects as high as forty. Another thing worth noting is that a dataset with relatively less subjects does not necessarily correspond to a higher identification rate, such as the NSRDB dataset, due to high variability of individual heart behaviors and blind segmentation operations. But these four datasets all correspond to a identification rate no less than 94.5%, and own an average identification rate of 90.5%, demonstrating the effectiveness of the proposed algorithm. For four abnormal ECG datasets with severe heart diseases, the confusion matrices in Fig. 7 show that there are slightly increased false positives and false negatives, due to a much higher variability of the heartbeat morphologies. As shown in Table I, there are difference kinds of heart diseases in these four datasets, corresponding to ST depression/elevation, arrhythmia with other 18 kinds of diseases, atrial fibrillation, malignant ventricular arrhythmia, respectively. Therefore, it is much more challenging to learn the underlying patterns of these time-varying abnormal heartbeat behaviors. The bottom part of Table II gives the identification rate for these four abnormal datasets, which is from 86.6% to 93.9%. The average identification rate is 93.5%, which is still an attractive result, considering that our user identification approach is directly performed on randomly chosen ECG segments using automatically learned features from raw data of ECG signal.

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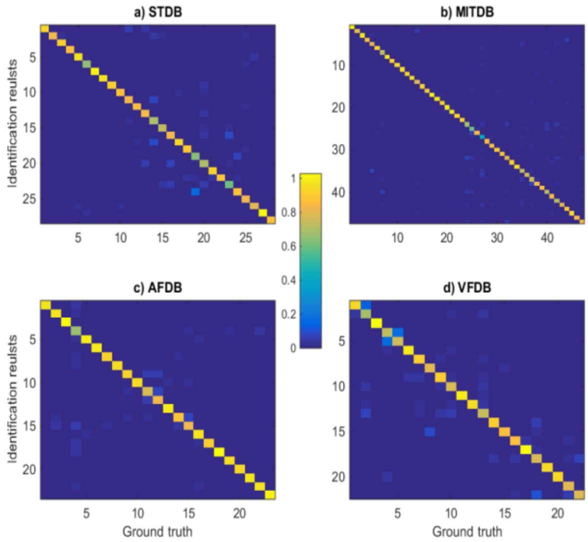

Fig. 7 Confusion matrix for human identification based on testing data of four abnormal ECG datasets with severe heart diseases

IV. CONCLUSION

In this paper, we have proposed a novel multi resolution convolutional neural network for Heart Disease Detection applications. Focusing on existing challenges, we have introduced blind signal processing and automatic feature learning techniques to effectively lower the algorithm engineering effort and also highly enhance the generalization ability of the algorithm. Our contributions include: 1) blindly select the signal segment for Heart Disease Detection purpose, which effectively avoids complicated and data-dependent signal event identification (e.g., ECG R peaks) and segmentation effort; 2) enrich the time-frequency representation by transforming data from the time domain to the wavelet domain, and remove phase difference among random-chosen signal segments by the auto-correlation approach; 3) introduce a parallel 1D-CNN to automatically learn multi-scale feature hierarchies from the wavelet domain raw data. This paper is expected to demonstrate that the proposed blind signal processing and deep learning techniques can effectively lower the algorithm engineering effort and provide a good generalization ability, for the biometric Heart Disease Detection applications.

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