

Deep Neural Network-based Person Identification using ECG Signals

Rudresh T K, Mallikarjun S H, Shameem Banu L

Abstract: In recent times, biometrics is mainly utilized for the authentication or identification of a user for a vast civilian application. Many electronic systems have been proposed that employ distinct behavioural or physiological human signatures for automatically identifying or verifying users. Currently, Electrocardiogram (ECG)-oriented biometric systems are in the exploratory stage. The behaviour of the ECG signal is distinctive to every person. As ECG is an exclusive physiological signal present only in living people, it is utilised in new biometric systems for recognising individuals and counteracting fraud and forgery attacks. The majority of traditional techniques are limited by restrictions in several points of detection in the ECG signal. The contribution of this paper is the enhancement of the novel person identification model using ECG signals. Initially, the ECG signal collected from the three benchmark sources undergoes pre-processing, during which noise is removed using a low-pass filter (LPF) approach. Furthermore, the Empirical Mode Decomposition (EMD) is employed for decomposing the signal. As feature selection is a significant part of classification enhancement, Principal Component Analysis (PCA) is used as a practical feature extraction method that selects the most critical features from the signal. Finally, the adoption of a Deep Neural Network (DNN) is performed as a deep learning model that can identify the exact person from the given ECG signal. The effectiveness of the method is extensively validated on benchmark datasets, yielding the desired outcome.

Keywords: Deep Neural Network, ECG signals, PCA-based Feature Selection, Person Identification, Signal Decomposition.

I. INTRODUCTION

The individual verification with the help of behavioural characteristics or physiological data has gained much interest owing to its vast discriminative contents [6]. The accurate and automatic identification of humans appears to be a significant challenge for modern society. As internet connections are enhanced, the need for maintaining accessibility and privacy for distinct resources has increased,

Manuscript received on 21 July 2023 | Revised Manuscript received on 28 July 2023 | Manuscript Accepted on 15 August 2023 | Manuscript published on 30 August 2023. *Correspondence Author(s) driving the requirement for novel identification techniques. The exploitation of different biological features for the automated and safe identification is an interesting topic these days. Nowadays, physiological signals such as ECG are considered biometric features for person identification. Apart from the special information, they are also present in the live people, making the forge option not possible [7]. Therefore, several techniques are introduced for utilising the ECG signal as a biometric, which can be categorised into two groups: fiducial points-independent techniques and fiducial points-oriented techniques. The fiducial points describe the location of the T wave, QRS complex wave, and P wave [8]. Around 97% of heart diseases are observed by the visual inspection of the specialists [9]. This grammar-oriented cyclostationary signal is composed of the key information that is employed in the biometric systems [10]. Though ECG contains quasi-rhythmic characteristics, owing to the existence of the Heart Rate Variability (HRV), ECG is considered a stochastic signal. The ECG signal offers subject-dependent features because the heart system of everyone is distinctive concerning ventricular, atrial, and heart muscle activities [11].

ECG is mainly used for recognition, and several ECG algorithms are studied for personal identification [12]. When considering real applications, such as physiological or biological data, the measured signal contains various sources of variability. These irrelevant sources do not facilitate the identification of a low-dimensional representation related to the latent variable. A solution to this is the usage of a proper observation operator that is robust or invariant to these nuisance variability sources. The scattering transform [13] offers a representation that is stable to the deformation and is also used in several applications [14]. The deep learning algorithm is used in several fields because of its deep learning, yet it seems to be difficult to investigate its performance factors [15]. The test signal source is identified by training machine learning algorithms, but it is challenging to generalise, tune, and design for distinct cases.

The main contribution of this paper is:

- To develop the new structure of the person identification model with the help of the ECG signal by gathering three standard publicly available datasets, such as the ECG-1D database, MIT-BIH Arrhythmia Database, and PTB Diagnostic ECG Database.
- To remove the noise present in the signal using the LPF and to decompose the signal using the EMD, from which the features are selected using the PCA.

Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) © Copyright: All rights reserved.



Retrieval Number:100.1/ijeat.F42620812623 DOI: <u>10.35940/ijeat.F4262.0812623</u> Journal Website: <u>www.ijeat.org</u>

Rudresh T. K.*, Lecturer, Department of Electronics and Communication Engineering, Government Polytechnic, Chamarajanagar (Karnataka), India. E-mail: <u>tkrudresh@gmail.com</u>, ORCID ID: <u>0000-0001-8813-8239</u>

Mallikarjun S. H., Lecturer, Department of Electronics and Communication Engineering, Government Polytechnic, Kampli (Karnataka), India. E-mail: <u>vmakdree@gmail.com</u>, ORCID ID: <u>0000-0002-8807-9061</u>

Shameem Banu L, Lecturer, Department of Electronics and Communication Engineering, Government Polytechnic, Bellari (Karnataka), India. E-mail: <u>shamim.26@gmail.com</u>, ORCID ID: <u>0009-0005-1029-3710</u>

[©] The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an <u>open access</u> article under the CC-BY-NC-ND license <u>http://creativecommons.org/licenses/by-nc-nd/4.0/</u>

• To identify the exact person from the provided ECG signal by classification using the DNN and to prove the betterment of the proposed method by comparing it with other machine learning techniques.

The organisation of the paper is as follows: Section I provides an introduction to person identification using ECG signals. The literature on person identification using ECG signals is presented in Section II. The deep learning-based person identification using the EEG signal is explained in Section III. Section IV describes the enhanced person identification via EEG signal by DNN. Section V gives the results and discussions. Section VI provides the conclusion.

II. LITERATURE SURVEY

A. Related Work

In 2019, Neung and Chang [1] have considered the personal identification with the help of a Robust Eigen ECG Network (REECGNet). Generally, the usage in real-time scenarios and the performance of PCA were reduced by corrupted observations and limited robustness to outliers. It was mostly robust in the case of nonlinear data. The features were attained from the visual content without the use of back-propagation. The experimental outcomes demonstrated a recognition performance of 98.25%. Additionally, the superiority was shown by incorporating noise, resulting in a recognition rate of 97.5%.

In 2018, Boostani *et al.* [2] have proposed a fast-to-compute and effective ECG feature using the Empirical Mode Decomposition (EMD), and then the features such as entropy, amplitude, instantaneous phase, and instantaneous frequency were extracted from the final EMD component. It was compared to existing features, including PCA, wavelet coefficients, correlation, and fiducial points. It achieved 95% verification accuracy, offering a lower-dimensional feature space than its top-rank counterparts.

In 2018, Yousofvand *et al.* [3] have addressed a novel ECG-oriented identification algorithm. Initially, the most reliable and significant fiducial point was identified. The redundant information was minimized by quantizing the ECG signal. In the final step, the ECG samples between two successive fiducial R points were coded and normalised using character strands symbolically. The ECG was linked to the authorised user with the maximum similarity. It was validated over 100 subjects, and it showed 99.4% identification accuracy.

In 2020, Jyotishi and Dandapat [4] have modelled a novel Long Short-Term Memory (LSTM)-oriented framework for the person identification with the help of ECG signal. The underlying temporal representation was understood with consideration of the inter-beat and intra-beat variations. The LSTM captured the inter-beat variations for the smaller ECG segments. The detection of fiducial points was not needed. It was achieved by the LSTM training network using a smaller ECG signal segment. It was validated against four databases, including CYBHi, ECG-ID, the MIT-BIH arrhythmia database, and PTB. It attained 97.3% accuracy of the PTB database for 290 subjects. The CYBHi returned 79.37% accuracy.

In 2017, Sulam *et al.* [5] have developed a framework for the identification as well as classification based on a manifold

Retrieval Number:100.1/ijeat.F42620812623 DOI: <u>10.35940/ijeat.F4262.0812623</u> Journal Website: <u>www.ijeat.org</u> learning algorithm. It described the natural organisation as a dynamic function. The diffusion maps algorithm was leveraged using a specific manifold learning technique that not only differentiated among the distinct states of a similar system but also discriminated between distinct systems. A classification strategy was developed based on the distance motion among the embedded sample distributions for different classes, and three forms of calculating these separations were also established. This technique attained 97.25% recognition accuracy over 90 subjects.

B. Review

It is clear that biological signals of every subject, such as the ECG signal, carry their signature. Various trials are conducted to extract subject-dependent features, taking into account human verification. Apart from several efforts to characterise ECG signals and achieve the best outcomes for low populations, the behaviour of traditional techniques fails due to the availability of arrhythmias or noise. Table 1 shows the features and challenges associated with the conventional person identification using ECG signals. REECGNet [1] achieves a better recognition rate and also enhances the performance via the scalar transformation. But, the performance is not improved by adjusting the SG size and the RPCA's lambda coefficient. EMD and kNN [2] generate only less count of features and also achieves better outcomes concerning mean verification rate. Still, various time-changing features are not incorporated to minimise the computational burden in the decomposition process. DTW [3] attains maximum similarity and identification accuracy and also returns a better precision rate. Yet, the hardware, such as an FPGA, is not implemented for real-time applications. LSTM [4] attains better performance with minimum evaluation data and enrollment amount, and also, the fiducial point detection is not needed. But the multi-session ECG and off-the-person recordings are not considered. Diffusion maps algorithm and Scattering Transform [5] attains the highest reported outcomes for the utilized database and also quantifies the distance among the low-dimensional embedded samples. Still, it does not quantify the similarity using various sophisticated methods or definitions to enhance performance in the complex classification process. Hence, novel approaches must be adopted to identify individuals using ECG signals that can effectively overcome these challenges.

III. DEEP LEARNING BASED PERSON IDENTIFICATION

A. Proposed Model

Nowadays, the ECG biometric is an interesting topic for person identification. This is because the geometrical and physiological variations of the heart in distinct individuals reveal specific uniqueness in their ECG signals.

Yet, these biometric modalities are not robust against false identity and are not suitable for achieving better performance in terms of identification

accuracy, such as gait and keystroke. Researchers recommend various techniques for proving the

Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) © Copyright: All rights reserved.





robustness and reliability of ECG biometrics against identity falsification. Moreover, researchers are beginning to label conflicts with the help of deep learning approaches to improve robustness and recognition accuracy. The architectural description of the proposed model is shown in Fig. 1.



Fig. 1. Architecture of the proposed DNN-based person identification

The proposed DNN-based person identification using ECG signals consists of five phases: "data collection, pre-processing, signal decomposition, feature extraction, and classification". Initially, the ECG signals are gathered from three publicly available standard datasets. The gathered ECG signal data are passed to the second step of pre-processing for removing the noise present in the signals. Here, the pre-processing of ECG signals is performed using the low-pass filtering approach. This pre-processed ECG signal is given to the third phase of signal decomposition for further decomposition of the signal. Here, the signal decomposition is accomplished by the EMD. This decomposed ECG signal is subjected to the fourth phase of feature extraction for extracting the significant features present in the signal. Feature extraction is performed using the PCA technique. The extracted features are then passed to the final phase of classification, where the DNN serves as the deep learning model for identifying the exact person from the provided ECG signal.

B. Signal Pre-Processing

The signal preprocessing is performed to remove noise from the gathered signals. Assume the input signal as ZT_{jk}^{in} , in which $jk = 1, 2, \dots, JK$, where JK Represents the total number of signals present in the three datasets. Here, the preprocessing of the input signals is performed using the LPF technique. An LPF represents a filter that passes signals using a frequency less than a chosen cutoff frequency and attenuates signals having frequencies greater than the cutoff frequency. The accurate frequency response of the filter is based on the filter design. It represents the complement of a high-pass filter. Hence, the final pre-processed signal using the LPF is shown as ZT^{pre} .

C. Data Set Description

Here, three types of datasets are utilised for the proposed DNN-based person identification using ECG signals: the ECG-ID database, the MIT-BTH Arrhythmia database, and the PTB Diagnostic ECG database. Each of these datasets is described below.

ECG-1D database: This database is gathered from the link, "https://physionet.org/content/ecgiddb/1.0.0/". It is composed of 310 ECG recordings obtained from 90 individuals. Each recording is composed of information regarding recording date, gender, and age, 10 annotated beats, and ECG lead 1. The records were obtained from volunteers, comprising 46 women and 44 men, aged 13 to 75 years. Every record is composed of filtered and raw signals, such as signal 0, which is categorised as ECG 1 (raw signal), and signal 1, which is classified as ECG 1 filtered (filtered signal).

MIT-BIH Arrhythmia Database: This database is gathered from the link, "https://www.physionet.org/content/mitdb/1.0.0/#files-panel ". It is composed of 8 half-hour excerpts of two-channel ambulatory ECG recordings. The recordings were digitised at 360 samples per second per channel, with an 11-bit resolution

over a 10mV range. Every record was annotated

independently by two or multiple cardiologists. PTB Diagnostic ECG Database: This database is gathered the from link. "https://www.physionet.org/content/ptbdb/1.0.0/". It is achieved using a non-commercial, PTB prototype recorder with specifications that include noise level recording during signal collection, online recording of skin resistance, noise voltage with input short circuit, bandwidth, resolution, input resistance, input voltage, and 16 input channels. Every record involves 15 measured signals being measured simultaneously.

IV. ENHANCED PERSON IDENTIFICATION VIA DEEP LEARNING

A. EMD-based Signal Decomposition

The signal decomposition represents an efficient tool for assisting the recognition of modal information in the time-domain signals. Here, the pre-processed ECG signal ZT_{jk}^{pre} It is subjected to the signal decomposition phase, where the signal is decomposed using the EMD technique. EMD [16] is used for identifying the oscillatory modes available in the time scales that are described using the interval among the local extrema of the composite signal. The various steps for attaining the Intrinsic Mode Function (IMF) from a distorted signal are shown below.

Step 1: The local maxima as well as minima of the signal $ZT_{ii}^{pre}(te)$ Are found.

Step 2: Interpolate between maxima to find the upper envelope.

Step 3: Interpolate between minima to achieve a lower envelope.

Step 4: The mean of the upper as well as lower

Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) © Copyright: All rights reserved.



16

Deep Neural Network-based Person Identification using ECG Signals

envelopes me(te) They are calculated as in Eq. (1).

$$me(te) = \frac{\left(ee_{upper}(te) + ee_{lower}(te)\right)}{2} \tag{1}$$

In the above equation, $ee_{upper}(te)$ represents the upper envelope and $ee_{lower}(te)$ represents the lower envelope of the signal $ZT_{ik}^{pre}(te)$.

Step 5: Extract as in Eq. (2).

$$ce_1(te) = ZT_{jk}^{pre}(te) - me(te)$$
(2)

Here, the term $ce_1(te)$ Represents the IMF if it fulfils two conditions as below.

Condition 1: The count of local extrema of $ce_1(te)$ Is different from or equal to the count of zero crossings of $ce_1(te)$ By one.

Condition 2: The average of $ce_1(te)_{\text{It}}$ is logically assumed to be zero. If $ce_1(te)$ Does not satisfy these two conditions, then the steps from 1 to 4 are repeated on $ce_1(te)$ rather than $ZT^{pre}(te)$.

Step 6: The residue $re_1(te)$ It is computed as in Eq. (3).

$$re_{1}(te) = ZT_{jk}^{pre}(te) - ce_{1}(te)$$
(3)

Step 7: If the value of $re_1(te)$ Exceeds the threshold error tolerance value, then steps 1 to 7 are repeated to attain the new residue, as well as the subsequent IMF. If *ne* The count of the IMF is obtained through an iterative process, and then the original signal is reconstructed as shown in Eq. (4).

$$ZT_{jk}^{dec}(te) = \sum_{ne} ce_{ie}(te) + re(te)$$
(4)

Hence, the final decomposed signal is represented as ZT_{ik}^{dec} Respectively.

B. PCA-based Feature Extraction

Feature extraction is a technique that calculates the preselected features of ECG signals to be subjected to a processing scheme, such as a classifier, for enhancing the performance of an ECG-oriented control system. Here, the features are extracted from the decomposed signal ZT_{jk}^{dec} Using the PCA technique. PCA is a familiar statistical approach for signal analysis employed in several research fields. Here, PCA transforms the *ns* correlated variables into a *ds* (*ds* << *ns*) Uncorrelated variables are known as the principal components (PCs). Assume a dataset of *MS* connection vector is shown by *NS* Features. The steps for the PC calculation are shown as follows: The average μ The dataset is measured. Ured as in Eq. (5).

$$\mu = \frac{1}{MS} \sum_{is=1}^{MS} v s_{is} \tag{5}$$

The deviation from the average is shown as in Eq. (6).

$$\theta_{is} = v s_{is} - \mu \tag{6}$$

17

The sample covariance matrix of the dataset is shown in Eq. (7).

Retrieval Number:100.1/ijeat.F42620812623 DOI: <u>10.35940/ijeat.F4262.0812623</u> Journal Website: <u>www.ijeat.org</u>

$$CS_{ns \times ns} = \frac{1}{MS} \sum_{is=1}^{MS} \theta_{is} \theta_{is}^{T} = \frac{1}{MS} ASAS^{T}$$
(7)

Here, $AS = [\theta_1, \theta_2, \theta_3, \dots, \theta_{ns}]$. Assume US_{ks} as the ks^{th} eigenvector of CS, λ_{ks} as the related eigenvalue and $US_{ns \times ds} = [US_1US_2 \cdots US_{ds}]$ As shown in Eq. (8), the matrix of these eigenvectors is

$$CSUS_{ks} = \lambda_{ks} US_{ks} \tag{8}$$

The eigenvalues are ordered in decreasing order, and choose the eigen vectors, also known as principal components PC_{is} With the most significant eigenvalues. The principal component count is based on the inertia ratio as in Eq. (9).

$$\lambda = \frac{\sum_{is=1}^{ds} \lambda_{is}}{\sum_{is=1}^{ns} \lambda_{is}} \tag{9}$$

This ratio shows the information rate attained from the entire rough input data through the related ds Eigenvalues. Consider. ts as a new sample column vector, then the projection of ts The new subspace is spanned using PC_{is} As in Eq. (10).

$$ys_{is} = US_{is}^{T}ts \tag{10}$$

Hence, the finally extracted features from PCA are defined by Fet_{sm}^{pca} , in which $sm = 1, 2, \dots, SM$, where *SM* Represents the total number of features extracted using the PCA from the decomposed signal.

C. DNN-based Person Identification

The DNN is used for performing the classification regarding person identification. Here, the input to the DNN is the extracted PCA features. DNN [20] consist of three primary components like, "input layer, output layer, and hidden layers". It is defined with two hidden layers to understand the mapping association between the output and input data. Due to the increased number of training iterations, it fits the decision boundary of the labelled training data in a continuous manner. The training speed and the classification accuracy are improved by constructing two hidden layers. While considering the hidden layer, the total node count is evaluated as in Eq. (11).

$$nr = \sqrt{ar + br} + cr \tag{11}$$

In the above equation, a constant value is shown as cr The output layer node count is shown as br The hidden layer node count is shown by nr, and the input layer node count is shown by ar Respectively. The non-linear fitness capability is enabled as an activation function and included in the hidden layer. The sigmoid function is utilised as an activation function, as shown in Eq. (12).

$$SR = \frac{1}{1 + e^{-Fet_{sm}^{pca}r}}$$
(12)

Here, the input data of the network is shown as Fet_{sm}^{pca} And it is activated using the mapping function MR_{fr} Respectively, as in

Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) © Copyright: All rights reserved.





Eq. (13).

$$MR_{fr} = sigm(\omega_{ir}Fet_{sm}^{pca} + \beta_{ir})$$
(13)

In the above equation, the weight matrix and the bias are shown by ω and β Respectively. Hence, the final classified output from DNN returns the identified person as output.

V. RESULTS AND DISCUSSION

A. Experimental Setup

The proposed DNN-based person identification using ECG signals was implemented in MATLAB 2020a, and the results were collected. The dataset was collected from three standard, publicly available datasets. The proposed DNN-based person identification was compared with several machine learning algorithms, such as NN [19], SVM [18], and DT [17] in terms of performance measures such as, "accuracy, sensitivity, specificity, precision, FPR, FNR, FDR, NPV, F1 Score, and MCC" to determine the betterment of the proposed model.

B. Accuracy Analysis

The accuracy analysis of the proposed DNN-based person identification method and existing methods is displayed in Fig. 2 for the three datasets. From Fig. 2(a), at a 40% learning percentage, the accuracy of the DNN for dataset 1 is 1.37%, 1.80%, and 0.94% higher than that of NN, SVM, and DT, respectively. While considering Fig. 2(b), for dataset 2, the accuracy of the DNN at a 30% learning percentage is 0.31%, 2.21%, and 1.26% higher than that of the NN, SVM, and DT, respectively. In Fig. 2(c), for dataset 3, at a 60% learning percentage, the accuracy of the DNN is 1.59%, 0.42%, and 1.37% higher than that of NN, SVM, and DT, respectively. Hence, the accuracy analysis for the three datasets is better with the DNN than with the other methods.



Fig. 2(a)



Fig. 2. Accuracy analysis of the DNN and the existing machine learning algorithms-based person identification for "(a) Dataset 1, (b) Dataset 2, and (c) Dataset 3"

Fig. 2(c)

4 Learning Percentage 5

6

C. F1 Score Analysis

2

3

0.95

0.945

0.94

0.935

The F1 Score analysis of the proposed DNN-based person identification and the traditional algorithms for the three datasets is portrayed in Fig. 3. In Fig. 3(a), for dataset 1, the F1 Score of the DNN at 20% learning percentage is 0.51%, 0.71%, and 0.10% superior to NN, SVM, and DT respectively. Upon considering Fig. 3(b), for dataset 2, the F1 Score of the DNN at a 50% learning percentage is 1.65%, 1.33%, and 0.10% better than that of the NN, SVM, and DT, respectively. From Fig. 3(c), for dataset 3, the F1 Score of the DNN at a 10% learning percentage is 0.92%, 1.13%, and 1.44%, surpassing those of NN, SVM, and DT, respectively. Therefore, the F1 Score holds for the DNN-based person identification compared to other methods for the three datasets, respectively.

Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) © Copyright: All rights reserved.



Retrieval Number: 100.1/ijeat. F42620812623 DOI: 10.35940/ijeat.F4262.0812623 Journal Website: <u>www.ijeat.org</u>

18





The overall performance analysis for the DNN-based person identification and the existing algorithms for the three

datasets is displayed in Tables I, II, and III, respectively. From Table I, for dataset 1, the accuracy of the DNN is 2.81%, 1.70%, and 3.21% better than that of the NN, SVM, and DT, respectively. The F1 Score of the DNN is 1.5%, 0.87%, and 1.65% higher than those of NN, SVM, and DT, respectively. Considering Table I for dataset 2, the accuracy of the DNN is 3.06%, 2.2%, and 0.15% higher than that of NN, SVM, and DT, respectively. The precision of the DNN is 0.20%, 0.11%, and 0.08% better than that of NN, SVM, and DT, respectively. In Table III, for dataset 3, the accuracy of the DNN is 1.31%, 0.92%, and 1.31% superior to that of NN, SVM, and DT, respectively. Similarly, the specificity of the DNN is 2.63%, 2.63%, and 0.01% higher than that of NN, SVM, and DT, respectively. Therefore, the performance analysis holds better outcomes with the DNN-based person identification than the state-of-the-art algorithms.



Fig. 3. F1 Score analysis of the DNN and the existing machine learning algorithms-based person identification for "(a) Dataset 1, (b) Dataset 2, and (c) Dataset 3"

Table 1. Overall Performance Analysis with The DNN and The Existing State-of-the-Art Learning Algorithms-Based
Person Identification in Terms of Dataset 1

Performance Measures	DT [17]	SVM [18]	NN [19]	DNN [20]
NPV	0.48649	0.5	0.52632	0.5
Sensitivity	0.95811	0.97328	0.96113	0.98933
FNR	0.041889	0.026718	0.038872	0.010671
MCC	0.32095	0.40595	0.36118	0.5241
Precision	0.98512	0.98456	0.98593	0.98557
F1 Score	0.97143	0.97889	0.97337	0.98745
Specificity	0.48649	0.5	0.52632	0.5
FPR	0.51351	0.5	0.47368	0.5
Accuracy	0.94519	0.95926	0.94889	0.97556
FDR	0.014879	0.015444	0.014073	0.014427

19



Retrieval Number:100.1/ijeat.F42620812623 DOI: <u>10.35940/ijeat.F4262.0812623</u> Journal Website: <u>www.ijeat.org</u>



Table 2. Overall performance analysis with the DNN and the state-of-the-art machine learning algorithms-based person identification in terms of dataset 2

Performance Measures	DT [17]	SVM [18]	NN [19]	DNN [20]
Specificity	0.48649	0.51282	0.47368	0.5
FNR	0.014471	0.036613	0.041921	0.013699
F1 Score	0.98553	0.97416	0.97103	0.9863
Accuracy	0.97185	0.95037	0.94444	0.97333
FPR	0.51351	0.48718	0.52632	0.5
MCC	0.47202	0.3647	0.31575	0.4863
FDR	0.014471	0.014821	0.015662	0.013699
Precision	0.98553	0.98518	0.98434	0.9863
NPV	0.48649	0.51282	0.47368	0.5
Sensitivity	0.98553	0.96339	0.95808	0.9863

Table 3. Overall performance analysis with the DNN and the state-of-the-art machine learning algorithms-based person identification in terms of dataset 3

Performance Measures	DT [17]	SVM [18]	NN [19]	DNN [20]
Sensitivity	0.97405	0.97788	0.97407	0.98628
FNR	0.025954	0.022121	0.025934	0.01372
F1 Score	0.97928	0.98125	0.97929	0.9859
Precision	0.98457	0.98464	0.98458	0.98553
FDR	0.015432	0.015361	0.01542	0.014471
Accuracy	0.96	0.9637	0.96	0.97259
NPV	0.5	0.48718	0.48718	0.5
Specificity	0.5	0.48718	0.48718	0.5
MCC	0.41019	0.42064	0.39779	0.49262
FPR	0.5	0.51282	0.51282	0.5

VI. CONCLUSION

This paper presents a new structure for a person identification model using ECG signals. Initially, the signal was collected from three standard publicly available databases. Then, the preprocessing was done by the LPF, and the signal was decomposed using the EMD. Next, the PCA extracted the significant features from the decomposed signal. In the final step, the DNN has identified the exact person from the given ECG signal. According to the analysis, the accuracy of the DNN for dataset 1 was 2.81%, 1.70%, and 3.21% better than that of NN, SVM, and DT, respectively. Similarly, the specificity of the DNN for dataset 3 was 2.63%, 2.63%, and 0.01% higher than that of NN, SVM, and DT, respectively. Therefore, the DNN-based person identification using ECG signals yielded better outcomes than other existing techniques for the three datasets, respectively.

Funding/ Grants/ Financial Support	No, I did not receive.
Conflicts of Interest/ Competing Interests	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval or consent to participate, as it presents evidence that is not subject to interpretation.

Availability of Data and Material/ Data Access Statement	Yes, the Availability of Data and Material section tells the reader where the research data associated with an article is available and under what conditions the data can be accessed. They also include links (where applicable) to the dataset. https://physionet.org/content/ecgiddb/1.0.0/
Authors Contributions	All authors have equal participation in this article.

REFERENCES

Published By:

- Jae-Neung Lee; Keun-Chang Kwak, "Personal Identification Using a 1. Robust Eigen ECG Network Based on Time-Frequency Representations of ECG Signals", IEEE Access, vol. 7, pp. 48392 - 48404, March 2019. https://doi.org/10.1109/ACCESS.2019.2904095
- 2. R. Boostani, M. Sabeti, S. Omranian & S. Kouchaki, "ECG-Based Personal Identification Using Empirical Mode Decomposition and Hilbert Transform", Iranian Journal of Science and Technology, Transactions of Electrical Engineering, vol. 43, pp. 67-75, July 2018. https://doi.org/10.1007/s40998-018-0055-7
- 3. Leila Yousofvand, Abdolhossein Fathi & Fardin Abdali-Mohammadi, "Person identification using ECG signal's symbolic representation and dynamic time warping adaptation", Signal, Image and Processing, vol. 13, pp. 245-251, August Video Processing, vol. 13, pp. 245 https://doi.org/10.1007/s11760-018-1351-4 2018.
- 4. Debasish Jyotishi; Samarendra Dandapat, "An LSTM-Based Model for Person Identification Using ECG Signal", IEEE Sensors Letters, vol. 4, 2020 no. 8. August



Retrieval Number: 100.1/ijeat. F42620812623 DOI: 10.35940/ijeat.F4262.0812623 Journal Website: <u>www.ijeat.org</u>

20

Deep Neural Network-based Person Identification using ECG Signals

https://doi.org/10.1109/LSENS.2020.3012653

- Jeremias Sulam, Yaniv Romano, Ronen Talmon, "Dynamical system classification with diffusion embedding for ECG-based person identification", Signal Processing, vol. 130, pp. 403-411, January 2017. https://doi.org/10.1016/j.sigpro.2016.07.026
- G. Adam and P. Witold, "ECG Signal Processing, Classification and 6. Interpretation: A Comprehensive Framework of Computational Intelligence", London, U.K.: Springer-Verlag, 2012.
- R. G. Afkhami, G. Azarnia, and M. A. Tinati, "Cardiac arrhythmia classification using statistical and mixture modelling features of ECG signals," Pattern Recognit. Lett., vol. 70, pp. 45-51, Jan. 2016. https://doi.org/10.1016/j.patrec.2015.11.018
- S. Dutta, A. Chatterjee, and S. Munshi, ``Identication of ECG beats from 8. cross-spectrum information aided learning vector quantization," Measurement. vol 44, no. 10, 2020-2027, 2011. pp. https://doi.org/10.1016/j.measurement.2011.08.014
- 9. M. M. Tantawi, K. Revett, A.-B. Salem, and M. F. Tolba, "A wavelet feature extraction method for electrocardiogram (ECG)-based biometric recognition," Signal, Image Video Process., vol. 9, no. 6, pp. 1271-1280, Sep. 2015. https://doi.org/10.1007/s11760-013-0568-5
- 10. S. Wahabi, S. Pouryayevali, S. Hari, and D. Hatzinakos, "On evaluating ECG biometric systems: Session-dependence and body posture," IEEE Trans. Inf. Forensics Security, vol.. 9, no. 11, pp. 2002-2013, Nov. 2014. https://doi.org/10.1109/TIFS.2014.2360430
- 11. A. Ghaffari, M. R. Homaeinezhad, and M. M. Daevaeiha, "High resolution ambulatory Holter ECG events detection-delineation via modified multilead wavelet-based features analysis: Detection and quantification of heart rate turbulence," Expert Syst. Appl., vol. 38, no. 5299-5310, pp. May 2011. https://doi.org/10.1016/j.eswa.2010.10.028
- 12. K. T. Chui, K. F. Tsang, H. R. Chi, B.W. K. Ling, and C. K. Wu, "An accurate ECG-based transportation safety drowsiness detection scheme," IEEE Trans. Ind. Informat., vol. 12, no. 4, pp. 1438-1452, Aug. 2016. https://doi.org/10.1109/TII.2016.2573259
- 13. S. Padhy and S. Dandapat, "Third-order tensor-based analysis of multilead ECG for classification of myocardial infarction," Biomed. Signal Process. Control, vol. 31, pp. https://doi.org/10.1016/j.bspc.2016.07.007 71-78, Jan. 2017.
- 14. Y. Kutlu and D. Kuntalp, "Feature extraction for ECG heartbeats using higher order statistics of WPD coefficients," Comput. Methods Programs Biomed., vol. 105, no. 3, pp. 257-267, 2012. https://doi.org/10.1016/j.cmpb.2011.10.002
- 15. S.-M. Dima et al., "On the detection of myocardial scar based on ECG/VCG analysis," IEEE Trans. Biomed. Eng., vol. 60, no. 12, pp. 3399-3409, Dec. 2013. https://doi.org/10.1109/TBME.2013.227999
- 16. Papia Ray and Rajesh Kumar Lenka, "LOW FREQUENCY MODE ESTIMATION OF A DYNAMIC POWER SYSTEM BY NOISE ASSISTED EMPIRICAL MODE DECOMPOSITION", 2017 International Conference on Information Technology, IEEE Access, 2017.
- 17. H. Zhao and F. Kamareddine, "A Decision Tree Method on Fuzzy Name Identification from Chinese Phonemic Names to Chinese Names," 2018 International Conference on Computational Science and Computational Intelligence (CSCI), 2018, 227-232, 2018. pp. https://doi.org/10.1109/CSCI46756.2018.00050
- 18. R. Luhadiya and A. Khedkar, "Iris detection for person identification using multiclass SVM," 2016 IEEE International Conference on Advances in Electronics, Communication and Computer Technology (ICAECCT), 2016, 387-392, pp. 2016. https://doi.org/10.1109/ICAECCT.2016.7942619
- 19. M. Roukhami, M. T. Lazarescu, F. Gregoretti, Y. Lahbib and A. Mami, "Very Low Power Neural Network FPGA Accelerators for Tag-Less Remote Person Identification Using Capacitive Sensors," in IEEE Access, vol. 7, pp. 1022 https://doi.org/10.1109/ACCESS.2019.2931392 102217-102231, 2019
- 20. S. Ramesh, D. Vydeki, "Recognition and classification of paddy leaf diseases using Optimized Deep Neural network with Jaya algorithm", INFORMATION PROCESSING IN AGRICULTURE, September 2019. https://doi.org/10.1016/j.inpa.2019.09.002

AUTHORS PROFILE



Rudresh T. K. received a B.E. degree in Electronics and Communication Engineering from Visvesvaraya Technological University, Belagavi, Karnataka, India, in 2004, and an M.Tech degree in Electronics from the same university in 2008. He has been working as a Lecturer in the Department of Electronics and Communication Engineering at the Government Polytechnic,

Kampli, Karnataka, India, from 2011 to 2022. From 2023, he has been working as a lecturer in the Department of Electronics and Communication at Government Polytechnic, Chamarajanagara. Before that, he worked as a software engineer at L&T Integrated Engineering Services, Mysore, India, from 2007 to 2011. His research interests include signal processing, image processing, VLSI and the Internet of Things.



Mallikarjun S. H. received a B.E. degree in Electronics and Communication Engineering from Visvesvaraya Technological University, Belagavi, Karnataka, India, and an M.Tech degree in VLSI Design and Embedded Systems from the same university in 2008 and 2011, respectively. He has been working as a Lecturer in the Department of Electronics and Communication Engineering at the

Government Polytechnic, Kampli, Karnataka, India, since 2012. Before that, he worked as an Assistant Professor at AIT, Chickmagaluru, India, from 2011 to 2012. His research interests include medical electronics and image processing.



Shameem Banu L received a B.E. degree in Electronics and Communication Engineering from Visvesvaraya Technological University, Belagavi, Karnataka, India, in 2003, and an M.Tech degree in Digital Communication & Networking from the same university in 2019. She has worked as a Lecturer in the Department of Electronics and Communication Engineering at the Government

Polytechnic Ballari, from 2008 to 2012 and from 2012 to 2022 at the Government Polytechnic, Kampli, Karnataka, India. From 2023, she has been working as a lecturer in the Department of Electronics and Communication at Government Polytechnic, Ballari. Before that, she also worked as an Assistant Professor at RYMEC Ballari, India, from 2003 to 2008. Her research interests include Communication Systems and Image Processing.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of the Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)/ journal and/or the editor(s). The Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Retrieval Number: 100.1/ijeat.F42620812623 DOI: 10.35940/ijeat.F4262.0812623 Journal Website: www.ijeat.org

and Sciences Publication (BEIESP) © Copyright: All rights reserved.

Published By: