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Deep Neural Network-based Person Identification using ECG Signals

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Abstract: ***In recent times, biometrics is mostly utilized for the authentication or identification of a user for a vast civilian application. Most of the electronic systems have been proposed that employed distinct behavioral or physiological human beings signature for identifying or verifying the user in an automatic manner. Nowadays, Electro Cardio Gram (ECG)-oriented biometric systems are in the exploration stage. The behavior of the ECG signal is distinctive to every person. As ECG is an exclusive physiological signal that is present only in the live people, it is utilized in the new biometric systems for recognizing the people and to counter the fraud as well as the forge attacks. Majority of the traditional techniques limits from the restriction in several points detection in the ECG signal. The contribution of this paper is the enhancement of the novel structure of person identification model by ECG signal. At first, the ECG signal collected from the three benchmark source is subjected for pre-processing, in which the noise is removed by Low Pass Filter (LPF) approach. Further, the Empirical Mode Decomposition (EMD) is adopted for the decomposition of signal. As feature selection is the significant part of classification enhancement, Principle Component Analysis (PCA) is used as the effective feature extraction that takes the most important features from the signal. Finally, the adoption of Deep Neural Network (DNN) is performed as the deep learning model that could identify the exact person from the given ECG signal. The effectiveness of the method is extensively validated on benchmark datasets and retrieves the outcome.***

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

I. INTRODUCTION

The individual verification with the help of behavioral characteristics or physiological data has gained much interest owing to their vast discriminative contents [6]. The accurate as well as automatic human identification seems to be an important challenge for the recent modern society. When the internet connections are enhanced, the accessibility as well as the privacy maintenance to distinct resources has increased the requirement for the novel identification techniques. The exploitation of distinct biological features for the automated and safe identification is an interesting topic during these days. Nowadays, physiological signals like ECG are considered as the biometric features for the purpose of person identification. Apart from the special information, they are also present in the live people making the forge option as not possible [7]. Therefore, several techniques are introduced for utilizing the ECG signal as biometric that can be categorized into two groups such as the fiducial points-independent techniques and fiducial points-oriented techniques. The fiducial points describe the location of 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 as a stochastic signal. The ECG signal offers subject-dependent features because the heart system of everyone is distinctive with respect to ventricular, atrium, and heart muscle activities [11].

ECG is mostly used for the recognition, and several ECG algorithms are studied for the personal identification [12]. While considering the real applications such as the physiological or biological data, the measured signal contains various variability sources. These irrelevant sources do not allow finding 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 the deep running, yet it seems to be difficult for investigating its performance factors [15]. The test signal source is identified by training the machine learning algorithms but are hard to generalize, tune, and design to distinct cases.

The main contribution of this paper is:

- To develop the new structure of person identification model with the help of the ECG signal by gathering three standard publically 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.

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

The organization of the paper is: Section I provides the introduction regarding the person identification using ECG signals. The literature works of the person identification using ECG signals are given in Section II. The deep learning-based person identification using 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 gives 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 the real time scenarios and the performance of the PCA was lessened by the 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 that it revealed 98.25% recognition performance. Additionally, the superiority was described by including the noise, and it returned 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 the existing features like PCA, wavelet coefficients, correlation, and fiducial points. It returned 95% verification accuracy that offered lower dimensional feature space than the 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 among two successive fiducial R points were coded and normalized using the character strands in a symbolic manner. The ECG was linked to the authorized user containing 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 inter-beat variations were captured by the LSTM for the smaller ECG segments. The detection of fiducial points was not needed. It was attained by the LSTM training network with smaller ECG signal segment. It was validated on four databases such as CYBHi, ECG-ID, 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 on the basis of a manifold learning algorithm. It described the natural organization as a dynamics functions. The diffusion maps algorithm was leveraged using a specific manifold learning technique that not only differentiated among the distinct states of the similar system but also discriminated distinct systems together. A classification strategy was built on the basis of a distance motion among the embedded sample distributions for distinct classes, and also developed three forms of calculating these separations. 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 own self signature. Various trials are done for extracting the subject-dependent features with consideration of human verification. Apart from several efforts for characterizing the ECG signals and offering the best outcomes for the low population, the behavior of the traditional techniques fails in the availability of arrhythmia or noise. Table 1 shows the features and challenges liked with the traditional 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 enhanced by adjusting the SG size and the RPCA's lamda coefficient. EMD and kNN [2] generate only less count of features and also achieves better outcomes with respect to mean verification rate. Still, various time changing features are not incorporated for minimizing 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 FPGA is not implemented for the real-time application. LSTM [4] attains better performance with minimum evaluation data and enrolment 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 by various sophisticated ways or definitions for enhancing the performance in the complex classification process. Hence, novel methods must be adopted for identifying the persons using the ECG signals that can overcome these challenges in an effective way.

III. DEEP LEARNING BASED PERSON IDENTIFICATION

A. Proposed Model

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

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Yet, these biometric modalities are not robust against false identity and are inappropriate to offer better performance with respect to identification accuracy like gait and keystroke. Various techniques are recommended by the researchers for proving the robustness and reliability of the ECG biometric against the identity falsification. Moreover, researchers begin to label the conflicts with the help of deep learning approaches for improving the robustness and recognition accuracy. The architectural description of the proposed model is shown in Fig. 1.

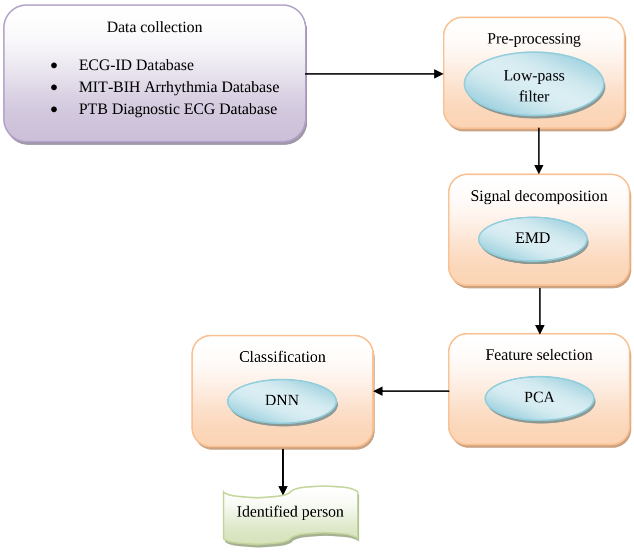

Fig. 1. Architecture of the proposed DNN-based person identification

The proposed DNN-based person identification using ECG signals consist of five phases such as, "data collection, pre processing, signal decomposition, feature extraction, and classification". Initially, the ECG signals are gathered from three publically available standard dataset. The gathered ECG signal data are given to the second step of pre processing for removing the noise that is present in the signals. Here, the pre-processing of ECG signals is done by the low pass filtering approach. This pre processed ECG signal is given to the third phase of signal decomposition for decomposing 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. The feature extraction is done using the PCA technique. The extracted features are given to the final phase of classification, in which the DNN is performed as the deep learning model for identifying the exact person from the provided ECG signal.

B. Signal Pre-Processing

The signal pre processing is done for removing the noise that is present in the gathered signals. Assume the input signal as ZT_{jk}^{in}, in which $jk = 1,2,\cdots,JK$, where JK represents the total number of signals present in the three datasets. Here, the pre processing of the input signals is done by the LPF technique. An LPF represents a filter that passes signals using a frequency lesser than a chosen cutoff frequency and attenuates signals having frequencies more 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 dataset are used for the proposed DNN-based person identification using ECG signals such as the ECG-ID database, MIT-BTH Arrhythmia database, and 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 that are being attained from 90 persons. Each recording is composed of information regarding recording date, gender, and age, 10 annotated beats, and ECG lead 1. The records were attained from the volunteers that consist of 46 women and 44 men in the age group of 13 to 75 years. Every record is composed of filtered and raw signals such as signal 0 that is categorized as ECG 1 (raw signal) and signal 1 that is categorized 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 digitized at 360 samples per second per channel having 11-bit resolution over a 10mV range. Every record was annotated independently using two or multiple cardiologists.

PTB Diagnostic ECG Database: This database is gathered from the link, "https://www.physionet.org/content/ptbdb/1.0.0/". It is attained by a non-commercial, PTB prototype recorder having specifications such as noise level recording during the collection of signals; online recording of skin resistance; noise voltage with input short circuit; bandwidth, resolution, input resistance, input voltage, and 16 input channels respectively. Every record involves 15 measured signals in a simultaneous manner.

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} is subjected to the signal decomposition phase, and the signal is decomposed with the help of 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 $ZT_{jk}^{pre}(te)$ are found.

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Step 2: Interpolate among maxima for attaining upper envelope.
Step 3: Interpolate among minima for attaining lower envelope.
Step 4: The mean of the upper as well as the lower envelope $me(te)$ are calculated as in Eq. (1).

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

In the above equation, $ee_{upper}(te)$ represents the upper envelope and $ee_{lower}(te)$ represents the lower envelope of the signal $ZT_{jk}^{pre}(te)$.
Step 5: Extract as in Eq. (2).

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

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 differ from or equal to count of zero crossing of $ce_1(te)$ by one.

Condition 2: The average of $ce_1(te)$ 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 $re_1(te)$ is computed as in Eq. (3).

$$re_1(te) = ZT_{jk}^{pre}(te) - ce_1(te) \tag{3}$$

Step 7: If the value of $re_1(te)$ exceeds the threshold error tolerance value, then the steps from 1 to 7 are repeated for attaining the new residue as well as next IMF. If ne count of IMF is attained from the iterative way, then the original signal is reconstructed as in Eq. (4).

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

Hence, the final decomposed signal is represented as ZT_{jk}^{dec} respectively.

B. PCA-based Feature Extraction

Feature extraction is a technique of calculating the preselected features of ECG signals to be subjected to a processing scheme like classifier for enhancing the performance of the 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 the signal analysis that is employed in several research fields. Here, PCA transforms the ns correlated variables into a ds $(ds << ns)$ uncorrelated variables known as the principal components (PCs). Assume a dataset of MS connection vectors as $vs_1, vs_2, vs_3, \cdots, vs_{MS}$, in which each connection vector is shown by NS features. The steps for PCs calculation are shown as follows: The average μ of the dataset is measured as in Eq. (5).

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

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

$$\theta_{is} = vs_{is} - \mu \tag{6}$$

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

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

Here, $AS = [\theta_1, \theta_2, \theta_3, \cdots, \theta_{ns}]$. Assume US_{ks} as the ks^{th} eigenvector of CS, λ_{ks} as the related eigen value and $US_{ns \times ds} = [US_1 US_2 \cdots US_{ds}]$ as the matrix of these eigenvectors as shown in Eq. (8).

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

The eigen values are ordered in the decreasing order and choose the eigen vectors also known as principal components PC_{is} with the largest eigen values. 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 eigen values. Consider ts as a new sample column vector, then the projection of ts to 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 is defined by Fet_{sm}^{pca}, in which $sm = 1, 2, \cdots, SM$, 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 the 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 for understanding the mapping association among the output and input data. Owing to the increased 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 I the hidden layer. The sigmoid is utilized as an activation function as in Eq. (12).

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

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 Eq. (13).

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

In the above equation, the weight matrix and the bias is 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 publically available dataset. The proposed DNN-based person identification was compared with several machine earning 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 the existing methods is displayed in Fig 2 for the 3 datasets. From Fig. 2(a), at 40% learning percentage, the accuracy of the DNN for dataset 1 is 1.37%, 1.80%, and 0.94% advanced than NN, SVM, and DT respectively. While considering Fig. 2(b), for dataset 2, the accuracy of the DNN at 30% learning percentage is 0.31%, 2.21%, and 1.26% higher than NN, SVM, and DT respectively. In Fig. 2(c), for dataset 3, at 60% learning percentage, the accuracy of the DNN is 1.59%, 0.42%, and 1.37% progressed than NN, SVM, and DT respectively. Hence, the accuracy analysis for the 3 datasets is better with the DNN than the other methods.

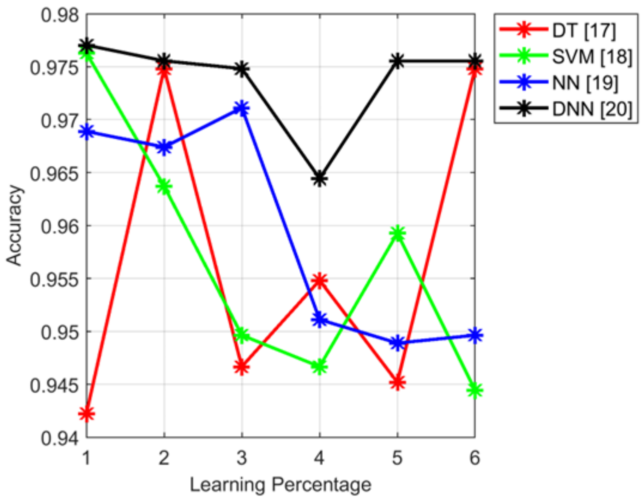

Fig. 2(a)

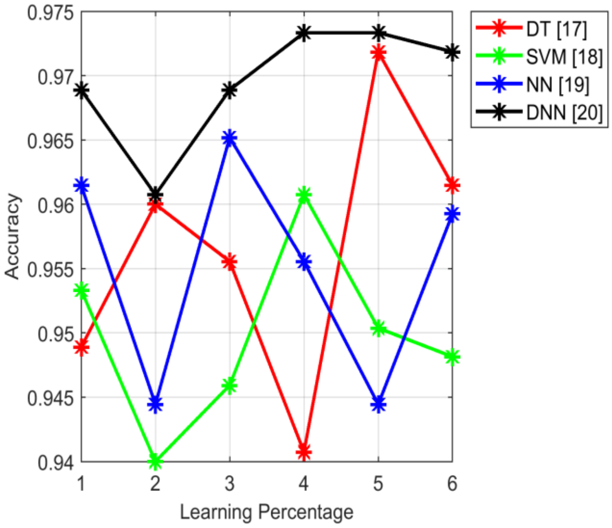

Fig. 2(b)

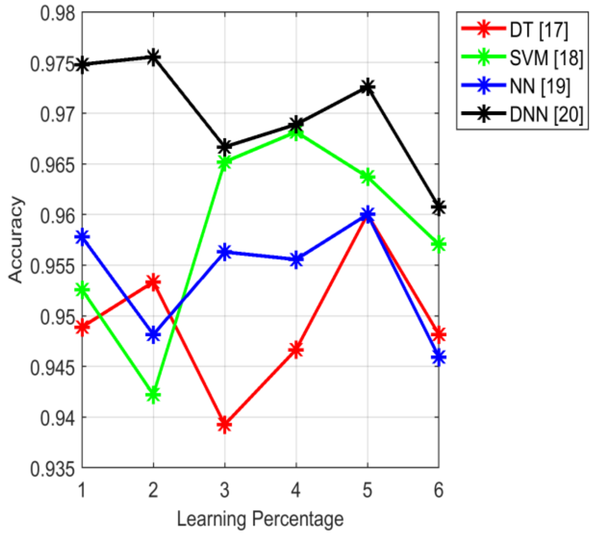

Fig. 2(c)

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"

C. F1 Score Analysis

The F1 Score analysis of the proposed DNN-based person identification and the traditional algorithms for the 3 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. On considering Fig. 3(b), for dataset 2, the F1 Score of the DNN at 50% learning percentage is 1.65%, 1.33%, and 0.10% better than NN, SVM, and DT respectively. From Fig. 3(c), for dataset 3, the F1 Score of the DNN at 10% learning percentage is 0.92%, 1.13%, and 1.44% surpassed than NN, SVM, and DT respectively. Therefore, the F1 Score holds good for the DNN-based person identification than the other methods for the 3 datasets respectively.

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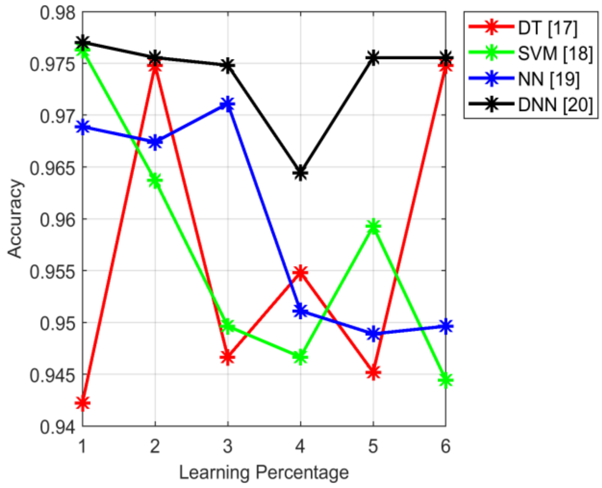

Fig. 3(a)

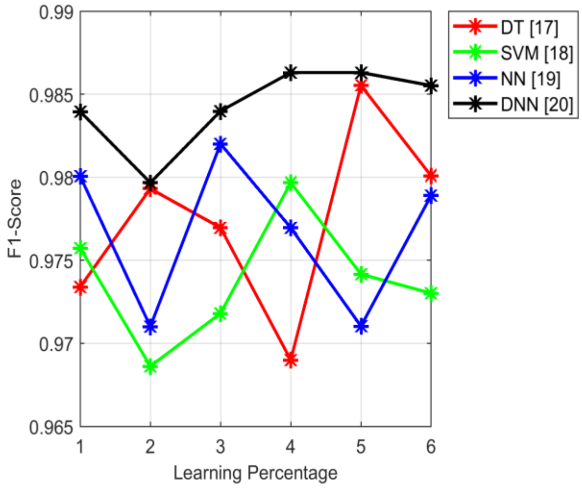

Fig. 3(b)

D. Overall Performance Analysis

The overall performance analysis for the DNN-based person identification and the existing algorithms for the 3 datasets is displayed in Table I, Table II, and Table III respectively. From Table I, for dataset 1, the accuracy of the DNN is 2.81%, 1.70%, and 3.21% better than NN, SVM, and DT respectively. The F1 Score of the DNN is 1.5%, 0.87%, and 1.65% progressed than NN, SVM, and DT respectively. On considering Table I, for dataset 2, the accuracy of the DNN is 3.06%, 2.2%, and 0.15% improved than NN, SVM, and DT respectively. The precision of the DNN is 0.20%, 0.11%, and 0.08% progressed than 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 NN, SVM, and DT respectively. Similarly, the specificity of the DNN is 2.63%, 2.63%, and 0.01% higher than 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.

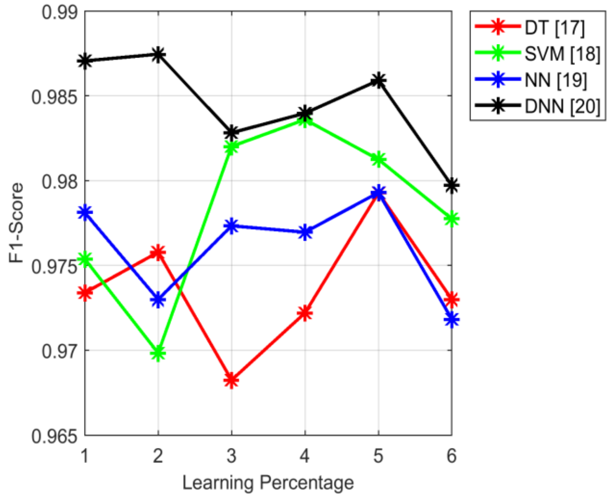

Fig. 3(c)

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

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 has developed the new structure of person identification model using ECG signal. Initially, the signal was collected from three standard publically available databases. Then, the pre processing was done by the LPF and the signal was decomposed by 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. From the analysis, the accuracy of the DNN for the dataset 1 was 2.81%, 1.70%, and 3.21% better than NN, SVM, and DT respectively. Similarly, the specificity of the DNN for dataset 3 was 2.63%, 2.63%, and 0.01% higher than NN, SVM, and DT respectively. Therefore, the DNN-based person identification using ECG signals proved better outcomes than the other existing techniques for the 3 datasets respectively.

DECLARATION

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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 and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Yes, Availability of Data and Material 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 data set. https://physionet.org/content/ecgiddb/1.0.0/
Authors Contributions	All authors have equal participation in this article.

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