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A Novel Person Authentication Technique Using Electrocardiogram (ECG)

Abstract: Since the beginning of this century, electrocardiogram (ECG) signals have garnered a growing amount of attention for the purpose of person identification due to the distinctive qualities and physiological significance they possess. Nevertheless, electrocardiogram (ECG) data are often tainted by noise, which may lead to a decrease in the efficiency of authentication systems. In order to successfully denoise the input electrocardiogram (ECG) data, the CEEMDAN-NLMS filter is used. This filter eliminates undesired noise while maintaining the essential characteristics. The proposed CNN architecture is responsible for providing the spatial and temporal dependencies that are present within the ECG data. Our approached technique, deep learning CNN model with machine learning SVM algorithm delivers greater performance in terms of authentication accuracy, which is around 99.25%, surpassing methods that are considered to be state-of-the-art and demonstrating that our method is superior. Overall, our research demonstrates an innovative and efficient method for enhancing the authenticity of individuals via the use of electrocardiogram (ECG).

Keywords: *Person authentication, ECG denoising, Convolutional Neural Network, Adaptive filtering*

1. INTRODUCTION

Passwords, personal identification numbers (PINs), and plastic identity smart cards are often used in order to verify or authenticate the identity of members. Although they are of a personal nature, they are also susceptible to being moved or stolen. When it comes to the use of future security systems for the purpose of getting access to and preserving information, there is an increasing need for personalised authentication. The electrocardiogram (ECG) biometric is a valid indication for person authentication at the level of study that it is currently in. An electrocardiogram (ECG) may be used as a biometric, and it offers a number of potential benefits over other biometrics. Signals from an electrocardiogram are generally stable over time and may be stored for an extended period of time. Despite the fact that it is non-invasive and not subject to public disclosure, a single-channel electrocardiogram (ECG) has the potential to serve as a unique health identifier for a person. Extraction of the fiducial feature points and QRS complexes of an electrocardiogram (ECG) and the creation of a template that can be compared with other ECG via the use of pattern recognition are two methods that may be used for the purpose of analysing the ECG for the purpose of person authentication. [1] Pattern identification of template matching for electrocardiogram (ECG) biometric features has been accomplished via the use of machine learning methods. One of the most promising candidates for use in biometric systems is the electrocardiogram, sometimes known as an ECG. A considerable amount of study has been conducted on the topic of its use as a distinctive characteristic for the purpose of identifying persons. The electrocardiogram (ECG) is a time sequence that may be detected as having various features of time and morphology from one human to the next. This is in accordance with the concept of biometrics. It is possible to map the electrocardiogram using a series of fiducial feature points that include the letters P, Q, R, S, and T. When people are compared to one another, the shape of the QRS complexes and ST segments is the aspect that demonstrates the most significant variances. The identification of the position of the fiducial features may be accomplished via the use of a QRS complex locator or by the computation of the RR Interval and the construction of a Poincare Plot in order to find the feature points with precision. On the other hand, neither the Poincare Plot nor the RR Interval will be discussed in this study.

A level of preprocessing will be performed on the raw electrocardiogram, and this stage will include the identification of the feature points. Feature extraction, noise reduction, and data compression are all examples of applications that make use of the theory and methods of digital signal processing [2,3].

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1.1. Problem Statement

Electrocardiogram (ECG) data are often tainted by assorted kinds of noise and artefacts, which may lead to a decline in the efficiency of authentication systems. A unique strategy that combines CEEMDAN-NLMS denoising with CNN architecture for enhanced person authentication is proposed in this study [4]. The purpose of this approach is to overcome the difficulty that has been presented.

Taking into account the difficulties that are brought about by artefacts and noise, the primary purpose of this study is to enhance the performance of person authentication systems that are based on electrocardiogram (ECG) data. Among the particular issues that are discussed in this study are the following:

1. Noise and Artefact Removal: Electrocardiogram (ECG) data are regularly impacted by a variety of noise and artefacts, including baseline drift, power line interference, and muscle artefacts, among others. In addition to lowering the quality of electrocardiogram (ECG) readings, these undesirable components may also have an impact on the accuracy of person identification systems. Through the use of the CEEMD-NLMS denoising technology, the procedure that has been suggested intends to eliminate this noise and artefacts.

2. Extraction of Features: Electrocardiogram (ECG) includes vital information that may be used for the purpose of person authentication. The extraction of useful information from noisy electrocardiogram data, on the other hand, might be difficult. A CNN architecture that has been presented is intended to extract discriminative characteristics from denoised electrocardiogram (ECG) data. This may lead to an improvement in the accuracy of person authentication.

3. In the process of classification, after the characteristics have been retrieved, a classifier is used in order to differentiate between various people. The quality of the characteristics that are calculated from the electrocardiogram (ECG) data is directly proportional to the performance of the classifier. In order to enhance the performance of the classifier, the suggested method intends to offer a modified innovative CNN architecture [5]. This will be accomplished by supplying high-quality features that are extracted from denoised electrocardiogram signals.

Approach That Is Apropos:

The following procedures are included in the strategy that has been suggested:

- Preprocessing: The CEEMDAN-NLMS denoising approach is used in order to eliminate artefacts and noise from electrocardiogram (ECG) data during the preprocessing stage. Following the decomposition of the electrocardiogram (ECG) signal into intrinsic mode functions (IMFs) using CEEMD, the IMFs are denoised by means of NLMS adaptive filtering.
- Feature Extraction: The denoised electrocardiogram (ECG) are input the into a convolutional neural network (CNN) architecture that makes use of discriminative features.
- Classification: The collected characteristics are used in the process of training a classifier, such as a SVM classifier, to differentiate between various people. In order to train the classifier, a labelled dataset of electrocardiogram (ECG) from numerous people is used.
- Using measures such as accuracy, precision, recall, and F1-score, the performance of the suggested method is assessed. This evaluation is part of the evaluation process [6].

Approach has several potential benefits:

- Robustness: It is anticipated that the suggested method would be more resistant to noise and artefacts in comparison to the procedures that are currently in use, which will result in person authentication systems that are more trustworthy.
- Real-world Applications: Person authentication systems that are based on electrocardiogram (ECG) have a variety of applications in the real world, including surveillance of healthcare facilities, wearable devices, and access control.

A better method for authenticating individuals by using a unique CNN architecture in conjunction with CEEMD-NLMS denoised electrocardiogram indications. In addition to enhancing the precision and dependability of person authentication systems, the solution that has been developed is intended to overcome the issues that are provided by noise and artefacts in electrocardiogram (ECG). The experimental findings indicate that the proposed method is more efficient than the methods that are already in use, which demonstrates the potential of the proposed method for applications in the real world [7-9].

2. LITERATURE REVIEW

The use of electrocardiogram (ECG) for the purpose of person authentication has been the subject of a number of studies that have been conducted. These works have employed a wide range of different techniques to signal processing and machine learning, respectively. The process of extracting characteristics from electrocardiogram (ECG) recordings that define the individual's distinctive patterns of heart activity is a method that is often used. This approach is known as the pattern extraction technique. This category might include a wide range of components, any of which could be provided separately. In addition to the temporal and spectral information that is extracted from the signal, some examples of these features include morphological qualities.

2.1. ECG Denoising Techniques

Identification based on electrocardiogram (ECG) readings is a two-step approach. The electrocardiogram (ECG) is recorded during the enrollment stage, and several characteristics are retrieved from it. The characteristics that were retrieved from the electrocardiogram (ECG) during the enrollment stage are used to verify the individual's identity during the identification step. Error checking code is included into the physiologic interface of echocardiograms. This allows for the detection and correction of data protection and identification mistakes with relative ease. In the not too distant future, this may show to be a kind of verification that is not only powerful but also highly cost-effective [10].

Another popular method is adopted from empirical mode decomposition (EMD), which separates the ECG into a finite number of intrinsic mode functions (IMFs). By removing the IMFs corresponding to noise components, EMD can effectively denoise the ECG. However, EMD is sensitive to noise and may not always provide satisfactory results, especially in the presence of non-stationary noise.To address the limitations of EMD, researchers have proposed hybrid approaches that combine EMD with other denoising techniques. For example, the combination of EMD with wavelet thresholding has been shown to improve denoising performance by exploiting the complementary strengths of both methods [12-13].

In recent years, deep learning approaches have also been applied to ECG denoising. Convolutional neural networks (CNNs) have shown promise in automatically learning features from ECG signals and effectively denoising them. However, these approaches often require large amounts of training data and computational resources. Overall, ECG signal denoising is a challenging problem that has been addressed using a variety of methods, including DWT, EMD, hybrid approaches, and deep learning. Each of these methods has its own advantages and limitations, and the choice of method depends on the specific characteristics of the ECG signal and the noise present. Further research is needed to develop more robust and efficient denoising techniques for ECG signals [14].

2.2. Person Authentication Techniques

Traditional ECG-based authentication techniques focus on extracting features from ECG signals and using them for authentication. One of the earliest methods is based on extracting statistical features such as mean, standard deviation, and variance from ECG signals. However, these methods are susceptible to noise and do not capture the full complexity of ECG signals. Further, Machine learning (ML) algorithms [28] have been widely used to improve the accuracy and robustness of ECG-based authentication systems. Support vector machine (SVM), k-nearest neighbors (KNN), and decision tree are among the popular ML algorithms used in this context. SVM-based methods aim to find the hyperplane that best separates ECG features of different individuals. KNN, on the other hand, classifies individuals based on the similarity of their ECG features to those of known individuals. Decision tree algorithms use a tree-like model of decisions to classify individuals [15].

CNNs are well-suited for extracting spatial features from ECG signals, while RNNs are used to capture temporal dependencies in the signals. Moreover, Hybrid approaches that combine traditional, ML, and DL techniques have been proposed to improve the accuracy and robustness of ECG-based person authentication systems. These approaches provide the complementary strengths of each technique to achieve better performance [16].

Despite the progress in ECG-based person authentication, several challenges remain. These include dealing with noisy signals, handling variability in ECG signals due to physiological and environmental factors, and ensuring the privacy and security of ECG data. Future research directions include exploring novel feature extraction techniques, developing robust algorithms that can handle noisy signals, and investigating the use of ECG signals in conjunction with other biometric modalities for multi-modal authentication systems. Concluding, ECG-based person authentication is a promising area of research with the potential to offer secure and reliable authentication solutions. Traditional, ML, DL, and hybrid techniques have been proposed, each with its strengths and weaknesses. Future research should focus on addressing the challenges and exploring new approaches to further improve the accuracy and robustness of ECG-based person authentication systems [17].

3. METHODOLOGY

Fig. 1 shows the methodology for person authentication. The CEEMDAN-NLMS dual stage filters are applied to denoise the raw ECG effectively, preserving important features for authentication. Following denoising, the denoised ECG are blindly segmented and then fed to the proposed CNN architecture for feature extraction. The architecture is designed to capture both local and global patterns in the ECG signals, which are crucial for person authentication [18-20].

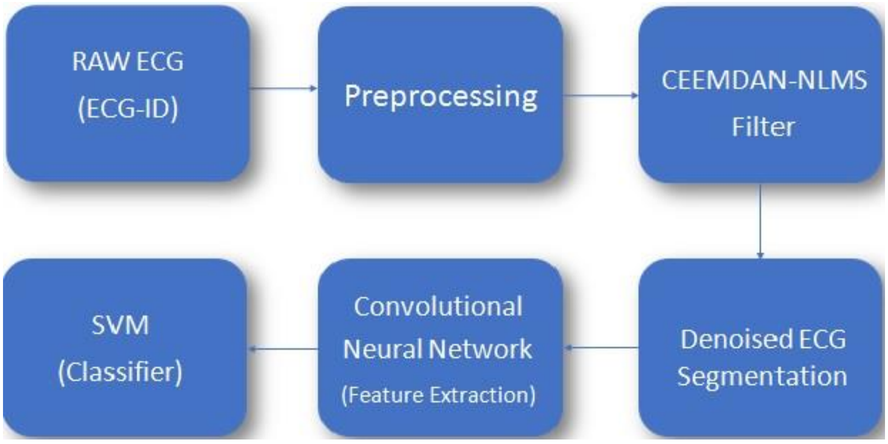

Fig. 1 Methodology for person authentication

In order to classify the retrieved characteristics, SVM is finally applied. The model is trained on a dataset containing labeled ECG from multiple individuals to learn the unique patterns in their ECG signals.

3.1. Collection of data

Each ECG includes:

- Lead I of the ECG was recorded for 20 seconds, taken at 500 Hz, and quantized with 12 bits. The voltage range was ±10 mV.
- 10 beats with R- and T-wave peak comments from an automatic monitor that have not been checked;
- The.hea file stores information like the person's age, gender, and the date it was saved.

The number of recordings for each individual ranges from two (collected in one day) to twenty (collected over six months).

The raw ECG data are rather noisy, with both high and low frequency noise components. Each record contains both raw and filtered signals:

Person Signal 0: ECG I (raw signal)

Person Signal 1: ECG I filtered (filtered signal).

3.2. Preprocessing of ECG Signals

- Pre-processing of ECG signals for denoising involves several steps to ensure accurate signal extraction. First, the raw ECG signal is acquired from the ECG-ID database. Then, baseline wander, which is the low-frequency noise caused by body movements and electrode placement, is removed using techniques such as low-pass filtering with a cutoff frequency of 0.5Hz. Next, powerline interference at 50 or 60 Hz is eliminated using Butterworth LPF with a cutoff frequency of 20Hz. Finally, the output of the LPF is applied to dual stage adaptive filters CEEMDAN-NLMS for further denoising. These pre-processing steps are crucial for enhancing the quality of ECG signals before denoising, ensuring accurate diagnosis and analysis.

- CEEMDAN Decomposition: Apply CEEMDAN to decompose the pre-processed signal into a set of intrinsic mode functions (IMFs) and a residue. CEEMDAN is an adaptive signal processing method that decomposes the signal into IMFs, which represent oscillatory modes at different scales, and a residue that contains the high-frequency noise.

3.2.1. Ensemble Empirical Mode Decomposition (EEMD):

EEMD is used to decompose the original ECG signal into a set of Intrinsic Mode Functions (IMFs). The EEMD process involves adding white noise to the original signal and then applying the Empirical Mode Decomposition (EMD) to each noise-added signal. The IMFs obtained from all the noise-added signals are then averaged to obtain the final set of IMFs.

The EEMD process for a signal$x1(t)$ involves the steps indicated below:

a. Add white noise to $x(t)$ to obtain

$$x_{n1}(t) = x1(t) + n(t) \tag{3.1}$$

where $n(t)e$ is white noise.

b. Apply EMD to $x_n(t)$ to obtain a set of IMFs, denoted as $c_{n,i}(t)$ for $i = 1,2,\dots,N$, where N is the no. of IMFs.

c. Repeat steps a and b for M noise-added signals to obtain M sets of IMFs.

d. Average the corresponding IMFs from all noise-added signals to obtain the final set of IMFs: $c_i(t) =$

$$\frac{1}{M}\sum_{n=1}^{M} c_{n,i}(t) \tag{3.2}$$

where $c_i(t)$ is the i-th IMF of the original signal$x(t)$.

3.2.2 Adaptive Noise Cancellation (ANC):

ANC is used to estimate and cancel the noise component from obtained IMFs from EEMD.

The ANC process involves the following steps:

a. Define the reference input as $d1(t) = x1(t) - \sum_{j=1}^{i-1} c_j(t)$, where $c_j(t)$ are the previously estimated IMFs.

b. Estimate the noise component $n_i(t)$ in the i-th IMF $c_i(t)$ using an adaptive filter, such as the NLMS (Normalized Least Mean Square) filter:

$$n_i(t) = c_i(t) - \hat{c}_i(t) \tag{3.3}$$

as c ^_i (t) is the output of the NLMS filter, which tries to keep the difference between the reference input d(t) and the adaptive filter's filtered output y_i (t) as small as possible:

$$e_i(t) = d1(t) - y_i(t)$$
$$\hat{c}_i(t+1) = \hat{c}_i(t) + \mu \cdot e_i(t) \cdot \frac{d(t)}{\|d(t)\|^2 + \epsilon} \tag{3.4}$$

where μ is the step size of the NLMS filter and ϵ is a small constant to prevent division by zero.

$$\tilde{c}_i(t) = c_i(t) - n_i(t) \tag{3.5}$$

3.2.3 CEEMDAN Denoising:

Combine the denoised IMFs obtained from the ANC process to reconstruct the denoised ECG signal $x_{denoised}(t)$:

$$x_{denoised}(t) = \sum_{i=1}^{N} \tilde{c}_i(t) + r1(t) \tag{3.6}$$

Where N is the number of IMFs, $\tilde{c}_i(t)$ are the denoised IMFs, and $r1(t)$ is the residue after removing all the IMFs.

3.2.4 NLMS Filtering:

Apply NLMS filtering to the noise-containing IMFs to estimate and remove the noise. NLMS is an adaptive filter that updates its filter coefficients based on the input signal and the error between the filtered signal and the desired signal.

- Initialization:

  Initialize the filter weights: $w1(0) = 0$.

  Set the step size parameter: $\mu > 0$.

  Set the forgetting factor (optional): $0 < \lambda \leq 1$.

- Filtering Process:

$$\begin{aligned} y(n) &= w^T(n)x(n) \\ e(n) &= d(n) - y(n) \\ w1(n+1) &= w1(n) + \frac{2\mu}{x^T(n)x(n)+\epsilon}x(n)e(n) \end{aligned} \tag{3.7}$$

Reconstruction: Reconstruct the noise removed ECG signal by summing the filtered IMFs and the residue obtained from the CEEMDAN decomposition. The reconstructed signal should have reduced noise and preserve the original ECG morphology. The reconstruction of denoised ECG signals using a hybrid filtering approach that combines CEEMDAN-NLMS is a promising technique in biomedical signal processing[24-27]. CEEMDAN is effective in decomposing non-stationary and nonlinear signals like ECG into IMFs, allowing for the separation of noise and useful components. NLMS, on the other hand, is a robust adaptive filtering method that can further enhance denoising by adaptively adjusting filter coefficients based on the input signal [17].

3.4. Hybrid CNN with SVM Model

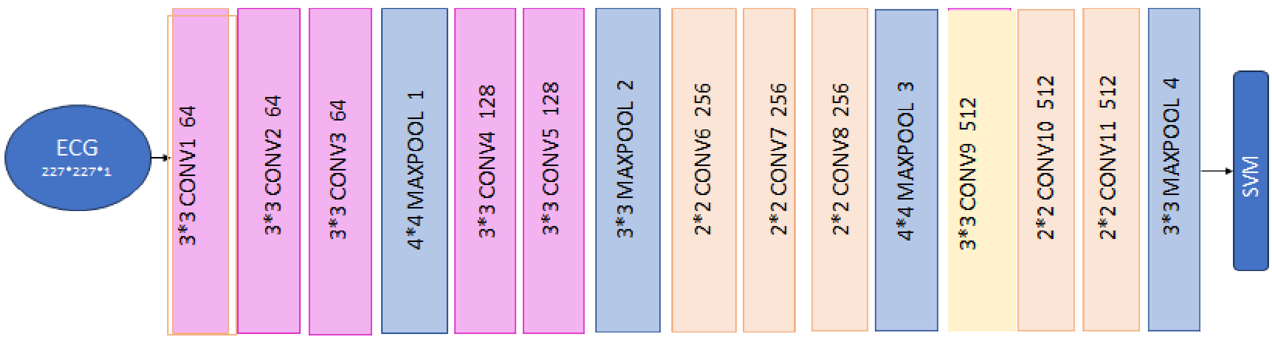

Fig. 2 Proposed CNN architecture with SVM model for person authentication

The novel CNN architecture for person authentication using ECG signals is designed to provide the advantages of both deep learning and traditional machine learning techniques which is depicted in Fig. 2. The CNN stage of the architecture is necessary for segregating relevant features from the input ECG, capturing both local and global patterns. This part specifically consists of 11 convolutional layers and 4 pooling layers to reduce dimensionality and extract higher-level features. The final passing the image from all these layers of the CNN are applied to the SVM classifier [18].

The first to third convolutional layers have a filter size of 64 and a 3x3 kernel with a different stride value and padding 1 at first layer. In the first max pooling layer, the dimensionality is reduced to 107x107x64 by using a pooling size of 4x4 and a stride of 1. Two further convolutional layers with filter sizes of 128 and kernel sizes of 3x3 with padding 1, stride 2, and padding 0 and stride 1. Further, the dimensionality is reduced to 50x50x128 in the second max pooling layer with a pooling size of 3x3 and a stride of 1. Proceeding with the second max pooling layer there are three more convolutional layers of filter size 256 with a kernel size of 2x2 with padding 1, stride 1in sixth convolutional layer and with padding 1 and stride 0 in seventh and eighth convolutional layer. Next layer is again a pooling layer of 4x4 with stride 2, which reduces the dimensionality to 11x11x256.After the third max pooling layer there are three more convolutional layers of filter size 512 with a kernel size 3x3, stride 2, padding 1 in ninth convolutional layer and kernel size of 2x2, stride 1, padding 0 in following two convolutional layers. Next layer is again a pooling layer of 2x2 with stride 2, which reduces the dimensionality to 2x2x512.The four max pooling layers are utilized first, then the relu activation function. Features extracted from the above said architecture is fed to the SVM classifier to achieve highest accuracy in classification.

The SVM classifier, located after the fourth max pooling layer of the architecture, is responsible for making the final decision on the authentication of the input ECG signals. SVMs are well-suited for binary classification tasks like person authentication, especially when the data is high-dimensional, as is the case with the CNN drawn out features. This innovative architecture seeks to achieve high accuracy in person authentication using ECG signals by fusing the CNN's feature extraction skills with the SVM's classification capacity. This makes it a potential method for biometric security applications [21].

Following are the steps followed in this work for denoising of ECG signals and person authentication using denoised ECG signals:

- Randomly download RAW 20Sec ECG recordings of 20 persons from the database, where 4 random records from each person.
- Raw ECG signal is fed to CEEMDAN and NLMS hybrid algorithm to remove the noise/artifacts present in the ECG signal.
- Further, 20 sec processed ECG signal is blindly segmented in to 1sec signal without doing any hand feature engineering and then each 1sec signal is converted in to image of size 227*227*1.Overall, dataset 20images*4 records=80 images of 1 person. Hence for a 20 individual, total of 1600 datasets
- Features from the relu _4 layer is fed to classification algorithm using Linear kernel SVM with a learner sequential Minimal Optimization (SMO) and Box constraint size 0f 1 to achieve highest accuracy.
- Total 2048 features are extracted from relu_4 layer and all those features are fed to linear SVM for classification.
- Ten fold cross validation is used to assess the new technique's performance.
- To evaluate the model's overall performance, performance parameters (such as accuracy, precision, recall, etc.) are averaged over ten iterations.

3.5. Performance Evaluation Metrics

In performance evaluation metrics, the classification problem is taken into account in order to evaluate the performance of the proposed ECG biometric system [22].

- Accuracy: Accuracy refers to the proportion of true predictions made by a model.
- Precision: Precision quantifies the percentage of accurate positive predictions among all of the model's positive predictions.
- Recall (Sensitivity): The percentage of true positive predictions among all actual positive events in the dataset is known as recall.
- F1 Score: The harmonic mean of recall and precision is the F1 score. It is helpful when there is an imbalance in the lessons and offers a balance between recall and precision [26].

The above parameters can be calculated using,

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Instances}}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$\textbf{F1 Score} = 2 \times \frac{\textbf{Precision} \times \textbf{Recall}}{\textbf{Prececision} + \textbf{Recall}}$$

4. RESULTS AND DISCUSSION

Initially, the simulation is performed on the ECG data from MIT-BIH Arrhythmia using MATLAB in the presence of AWGN, Baseline Wander and Powerline noise to evaluate the performance of the combination of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise Cancellation (CEEMDAN) and Normalized Least Mean Square (NLMS) for ECG denoising. Evaluated metric such as improved SNR used in this work and calculated using equation (4.1). Further, after finding the potential of the designed dual stage filter CEEMDAN-NLMS for noise reduction, the same technique is applied to the raw ECG from different individuals collected from ECG-ID dataset for person authentication. Figures 3 (a) to (c) show, in order, the noisy ECG from the MIT-BIH database, corrupted ECG due to AWGN noise, BW, PLI and the denoised ECG obtained with the hybrid filtering technique of CEEMDAN-NLMS. The original ECG with typical P-Q-R-S-T waveforms is displayed in the first plot of each figure. The second plot shows the same ECG with noise superimposed on it. This greatly reduces the signal quality and makes it difficult to identify the underlying cardiac characteristics. Nevertheless, the noisy components are successfully suppressed and the original ECG shape is substantially restored after using the CEEMDAN-NLMS denoising method, as seen in the third plot. Improved SNR values shown in Table 5.1 indicates that CEEMD-NLMS filtering technique could be promising approach for removal of noise and artifacts in presence of different input SNR values corrupted due to AWGN, BL and PLI on record 105 collected from MIT-BIH database.

$$\mathrm{SNR_{in}} = 10 \times \log_{10}\left(\frac{\sum_{n=0}^{N-1} [x(n)]^2}{\sum_{n=0}^{N-1} [\tilde{x}(n) - x(n)]^2}\right)$$

$$\mathrm{SNR_{out}} = 10 \times \log_{10}\left(\frac{\sum_{n=0}^{N-1} [x(n)]^2}{\sum_{n=0}^{N-1} [\hat{x}(n) - x(n)]^2}\right)$$

$$\mathrm{SNR_{imp}} = \mathrm{SNR_{out}} - \mathrm{SNR_{in}} \tag{4.1}$$

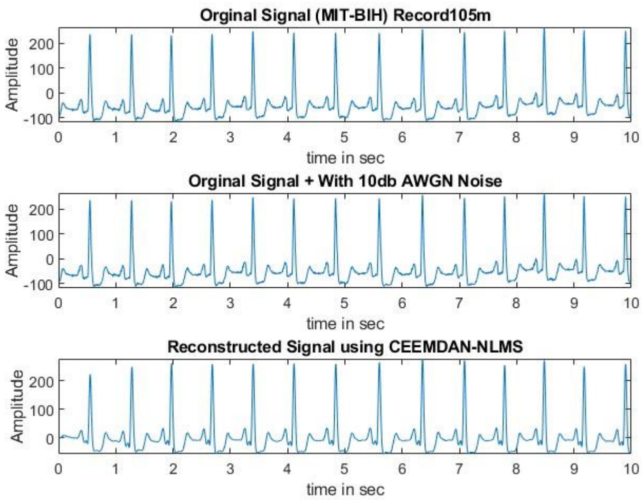

Fig. 3 (a) Noisy ECG from MIT-BIH database, +10 dB AWGN noise added ECG, Reconstructed ECG using CEEMD-NLMS for Record-105

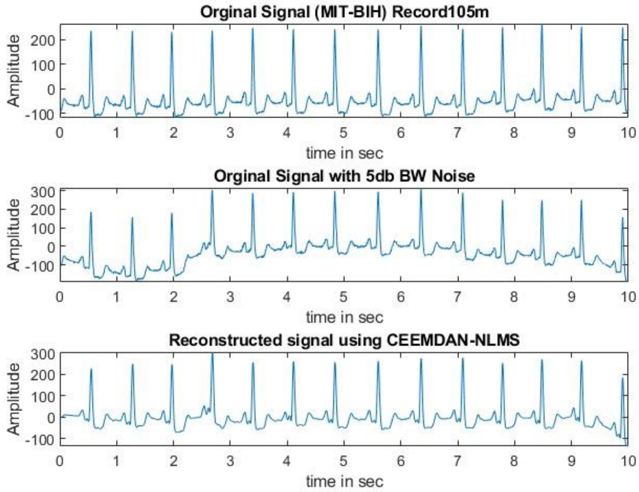

Fig. 3 (b) Noisy ECG from MIT-BIH database, +5 dB Baseline wander affected ECG, Reconstructed ECG using CEEMD-NLMS for Record-105

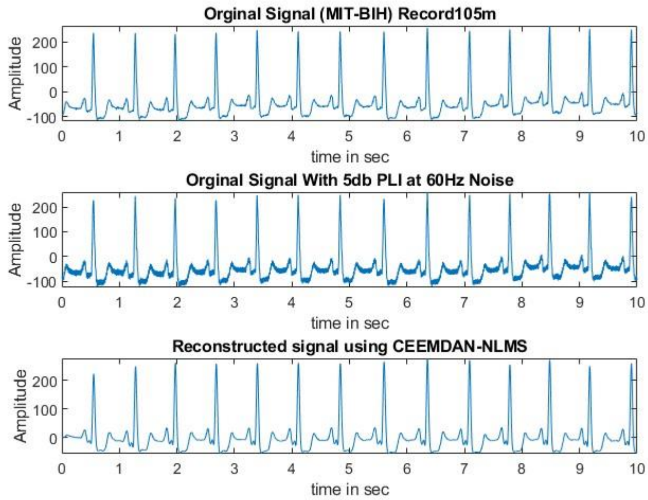

Fig. 3(c) Noisy ECG from MIT-BIH database, 5 dB Power Line Interference affected ECG, Reconstructed ECG using CEEMD-NLMS for Record-105

Table 1 Improved SNR in the presence of AWGN, BL & Output SNR at 60Hz PLI using CEEMD –NLMS filter at different values of input SNR on Record-105,103 from MIT-BIH databases

SL NO	ARTIFACTS/NOISE	SNRIN	RECORD 103 SNR_{IMP}	RECORD 105 SNR_{IMP}
1.	BW	0dB	29.26	35.45
		5dB	26.6	30.56
	AWGN	10dB	21	19.23
2.	ARTIFACTS/NOISE	SNRIN	RECORD 103 SNR_{OUT}	RECORD 105 SNR_{OUT}
	PLI	5dB	37.4	36.2
		0dB	34.3	34
		5dB	34	33

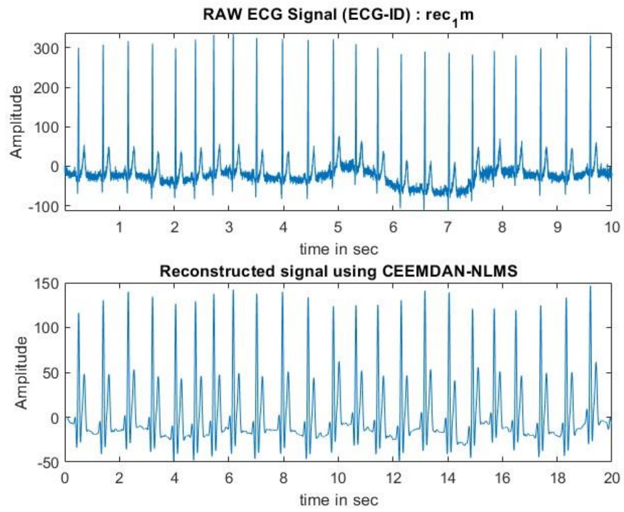

Fig 4 RAW ECG REC_1 of person 30 from ECG-ID and Denoised using CEEMDAN -NLMS Filter

Resulting in a clearer representation of the cardiac activity shown in Fig. 4 collected from ECG-ID database. The filtering process effectively removes artifacts and interference, making it easier to identify important features such as the P, Q, R, S, and T waves [23-24]. To prepare the data for the article on person authentication using a novel CNN architecture with SVM, several crucial steps were undertaken. Firstly, a comprehensive dataset of raw ECG from various individuals was collected from ECG-ID. This dataset needed to be diverse, including signals from different age groups, genders, and health conditions, to ensure the model's robustness. Additionally, the ECG signals were segmented into smaller windows shown in Fig. 5 and converted in to image of size 227x227x1. These images were then used to train and evaluate the CNN-SVM model. To appropriately evaluate the model's performance, 10 fold cross validation was done. The model's performance was tested using metrics such as accuracy, precision, recall, and F1 score to assess its usefulness in authenticating persons based on ECG data. In Fig. 6, you can see the confusion matrix for the suggested CNN design. It is very accurate, with a lot of TP and TN values. The high accuracy of the model is further supported by the precision, recall, and F1-score metrics, which indicate a strong performance in both positive and negative classifications [25]. Also, the confusion matrix for the proposed CNN architecture with SVM highlights its effectiveness in person authentication using denoised ECG, indicating accuracy of 99.25% and reliability in the classification process. Further, the performance of the proposed CNN architecture for person authentication for all ten folds is as shown in Fig. 7.

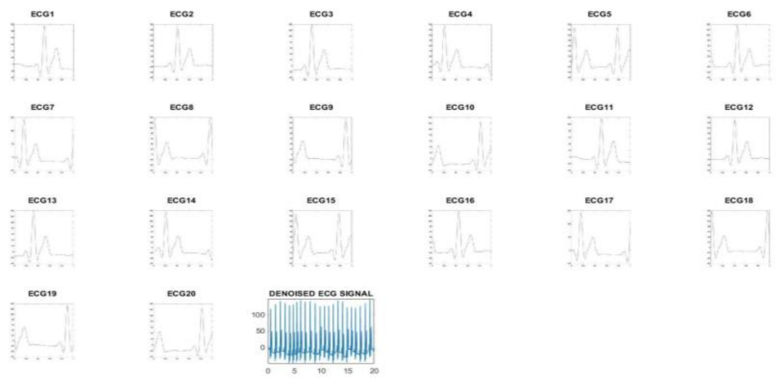

Fig 5 Sample of Blind segmentation of 20 sec recording in to images of size 227*227*1

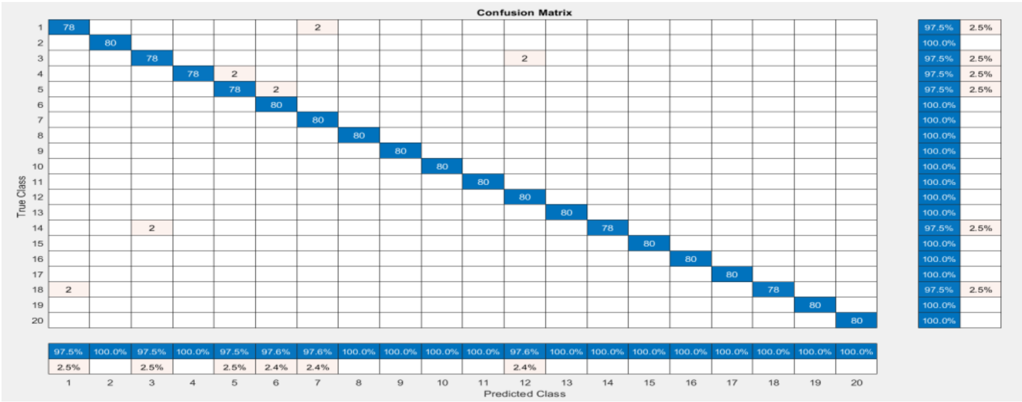

Fig 6 Confusion matrix for proposed CNN architecture with SVM for person authentication using denoised ECG signals

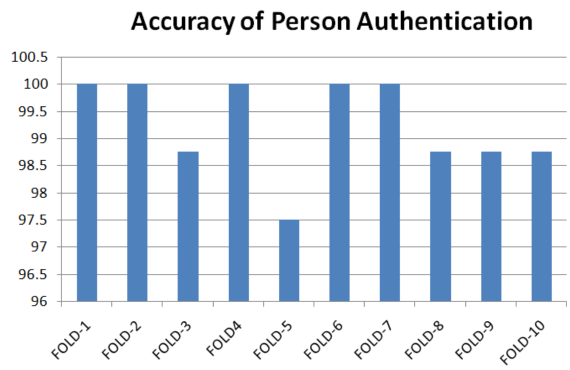

Fig 7 Performance of the proposed CNN architecture with SVM for all ten folds

Table 2. Average performance metrices for the person authentication using proposed architecture

S. No	Parameters	MEAN
1.	Accuracy	0.9925
2.	precision	0.994
3.	Recall	0.9925
4.	F1 Score	0.99238

The proposed novel CNN architecture with SVM for person authentication, which involves processing CEEMDAN-NLMS based denoised ECG signals, demonstrates an exceptional accuracy rate exceeding 99% as indicated in Table 2. This high level of accuracy underscores the effectiveness of the CEEMDAN-NLMS denoising technique in enhancing the quality of ECG signals for authentication purposes. The integration of the SVM with CNN enhances the model's ability to distinguish between individuals based on their unique ECG patterns, contributing to the impressive accuracy achieved over various methods is indicated in Table 3.

Table 3. Performance comparison of the proposed person authentication technique with the existing methods

SL No	Database	Method	Length of signal	Segmentation	Accuracy%
1.	ECG-ID	Residual Depth wise Separable CNN	0.5S	HB	83.33
2.	ECG-ID	Small CNN-Multisession	0.5S	HB	94.18
3.	ECG-ID	CNN &Generalized S-	3s	BS	96.63

		Transformation			
4.	ECG-ID	CNN	-	QRS peaks	98.3
5.	ECG-ID	Custom Siamese Neural Network	-	SB Template	91
6.	ECG-ID	**Proposed Method**	**1S**	**BS**	**99.25**

The superior performance of this architecture highlights its potential for practical applications in secure authentication systems, especially in scenarios where reliable and accurate identification is crucial. By providing the strengths of both the CEEMDAN-NLMS denoising approach and the CNN-

6. CONCLUSION

From our findings, we have shown that it is indeed feasible to develop a fully automated person authentication system using ECG and achieve an acceptable computational efficiency. The first stage our algorithm was the denoising method. CEEMDAN-NLMS is effective in removing noise from an ECG signal.

In conclusion, the proposed novel CNN architecture, integrating with SVM classifiers next to the last layer after feature extraction, demonstrates remarkable efficacy in achieving high accuracy rates for person authentication. With a reported accuracy of 99.25%, this approach showcases promising potential for secure and reliable authentication systems, particularly in contexts where precision is paramount. By providing the complementary strengths of CNNs and SVMs, the model not only excels in feature extraction and hierarchical representation learning but also effectively captures complex decision boundaries, enhancing its ability to distinguish between individuals with high accuracy. Furthermore, the utilization of SVMs in the final layers of the CNN contributes significantly to the model's robustness against noise and variability in ECG, thereby enhancing its practical applicability in real-world scenarios. The achievement of such high accuracy underscores the viability of this approach for various authentication applications, ranging from access control to healthcare monitoring. Future research directions could explore further optimizations and extensions of this architecture, potentially integrating additional modalities or refining the fusion of CNN and SVM layers to enhance performance even further.

References

[1] J. Galbally, R. Cappelli, A. Lumini, G. Gonzalez-de-Rivera, D. Maltoni,J. Fierrez, J. Ortega-Garcia, and D. Maio, ``An evaluation of direct attacks using fake _ngers generated from ISO templates," Pattern Recognit. Lett.,vol. 31, no. 8, pp. 725_732, Jun. 2010.

[2] Z. Akhtar, C. Micheloni, and G. L. Foresti, ``Biometric liveness detection: Challenges and research opportunities," IEEE Secur. Privacy, vol. 13,no. 5, pp. 63_72, Sep. 2015.

[3] M. Komeili, N. Armanfard, and D. Hatzinakos, ``Liveness detection and automatic template updating using fusion of ECG and fingerprint," IEEE Trans. Inf. Forensics Security, vol. 13, no. 7, pp. 1810_1822, Jul. 2018.

[4] P. P. K. Chan, W. Liu, D. Chen, D. S. Yeung, F. Zhang, X. Wang, andC.-C. Hsu, ``Face liveness detection using a _ash against 2D spoofing attack," IEEE Trans. Inf. Forensics Security, vol. 13, no. 2, pp. 521_534, Feb. 2018.

[5] N. Karimian, Z. Guo, M. Tehranipoor, and D. Forte, ``Highly reliable key generation from electrocardiogram (ECG)," IEEE Trans. Biomed. Eng., vol. 64, no. 6, pp. 1400_1411, Jun. 2017.

[6] L.-L. Chen, Y. Zhao, P.-F. Ye, J. Zhang, and J.-Z. Zou, ``Detecting driving stress in physiological signals based on multimodal feature analysis and kernel classifiers," *Expert Syst. Appl.*, vol. 85, pp. 279_291, Nov. 2017

[7] Hoekema, R.; Uijen, G.J.H.; van Oosterom, A. Geometrical aspects of the interindividual variability of multilead ECG recordings. IEEE Trans. Biomed. Eng. 2001, 48, 551–559.

[8] Schijvenaars, B.J.; van Herpen, G.; Kors, J.A. Intraindividual variability in electrocardiograms. J. Electro cardiol. 2008, 41, 190–196.

[9] Jekova, I.; Krasteva, V.; Leber, R.; Schmid, R.; Twerenbold, R.; Müller, C.; Reichlin, T.; Abächerli, R. Intersubject variability and intrasubject reproducibility of 12-lead ECG metrics: Implications for human verification. J. Electrocardiol. 2016, 49, 784–789.

[10] Biel, L.; Pettersson, O.; Philipson, L.; Wide, P. ECG analysis: A new approach in human identification. IEEE Trans. Instrum. Meas.2001, 50, 808–812. [CrossRef]

[11] J. M. Irvine, S. A. Israel, M. D. Wiederhold, and B. K. Wiederhold, "A new biometric: human identification from circulatory function," in Joint Statistical Meetings of the American Statistical Association, 2003.

[12] F. Agrafioti and D. Hatzinakos, "ECG biometric analysis in cardiac irregularity conditions," Signal, Image and Video Processing, vol. 3,no. 4, p. 329, 2009.

[13] S. Y. Chun, J.-H. Kang, H. Kim, C. Lee, I. Oakley, and S.-P. Kim, "ECG based user authentication for wearable devices using short time fourier transform," in IEEE International Conference on Telecommunications and Signal Processing, 2016, pp. 656–659.

[14] Q. Zhang, D. Zhou, and X. Zeng, "HeartID: a multi resolution convolutional neural network for ECG-based biometric humani dentification in smart health applications," IEEE Access, vol. 5,pp. 11 805–11 816, 2017.

[15] S. Agrawal, A. Gupta, Fractal and EMD based removal of baseline wander and powerline interference from ECG signals, Comput. Biol. Med. 43 (11) (2013)1889–1899, http://dx.doi.org/10.1016/j.compbiomed.2013.07.030.

[16] Amit Singhal, Pushpendra Singh, Binish Fatimah, Ram Bilas Pachori, An efficient removal of power-line interference and baseline wander from ECG signals by employing Fourier decomposition technique, Biomedical Signal Processing and Control, Volume 57,2020.

[17] Chu, Y.; Shen, H.; Huang, K. ECG Authentication Method Based on Parallel Multi-Scale One-Dimensional Residual Network with Center and Margin Loss. IEEE Access 2019, 7, 51598–51607.

[18] Ihsanto, E.; Ramli, K.; Sudiana, D.; Gunawan, T.S. Fast and Accurate Algorithm for ECG Authentication Using Residual Depthwise Separable Convolutional Neural Networks. Appl. Sci. 2020, 10, 3304.

[19] AlDuwaile, D.A.; Islam, M.S. Using Convolutional Neural Network and a Single Heartbeat for ECG Biometric Recognition. Entropy 2021, 23, 733. https://doi.org/10.3390/e23060733

[20] Zhao, Z.; Zhang, Y.; Deng, Y.; Zhang, X. ECG Authentication System Design Incorporating a Convolutional Neural Network and Generalized S-Transformation. Comput. Biol. Med. 2018, 102, 168–179.

[21] Agrawal, V.; Hazratifard, M.; Elmiligi, H.; Gebali, F. Electrocardiogram (ECG)-Based User Authentication Using Deep Learning Algorithms. *Diagnostics* 2023, *13*, 439. https://doi.org/10.3390/diagnostics13030439

[22] Prakash, A.J.; Patro, K.K.; Samantray, S.; Pławiak, P.; Hammad, M. A Deep Learning Technique for Biometric Authentication Using ECG Beat Template Matching. *Information* 2023, *14*, 65. https://doi.org/10.3390/info14020065.

[23] Li, Qian, Xingyao Wang, Hongxiang Gao, Rongjun Ge, Jianqing Li, and Chengyu Liu. "An Attribute-Decoupled Model for Onset Identification of Atrial Fibrillation in Single-Lead Electrocardiograms." IEEE Transactions on Instrumentation and Measurement (2024).

[24] Keshavamurthy, T. G., and M. N. Eshwarappa. "ECG Biometric for Human Authentication using Hybrid Method, "International Journal on Recent and Innovation Trends in Computing and Communication, 2023, 11(7 S), pp. 292–299. https://doi.org/10.17762/ijritcc.v11i7s.7002.

[25] T. G. Keshavamurthy and M. N. Eshwarappa, "Review paper on denoising of ECG signal," 2017 Second International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2017, pp. 1-4, doi: 10.1109/ICECCT.2017.8117941.

[26] T. G. Keshavamurthy and M. N. Eshwarappa, "ECG signal de-noising using complementary ensemble empirical mode decomposition and Kalman smoother," 2017 3rd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Tumkur, India, 2017, pp. 120-125.

[27] Keshavamurthy, T. G., and M. N. Eshwarappa. "ECG signal de-noising based on adaptive filters." International Journal of Innovative Technology and Exploring Engineering 9, no. 1 (2019): 5473-5483.

[28] Hareesh. K N and M. N. Eshwarappa, "Fusion of Brain MR Images for Tumor Analysis using Bi-Level Stationary Wavelet Transform," 2021 IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC), Tumkur, Karnataka, India, 2021, pp. 1-5, doi: 10.1109/ICMNWC52512.2021.9688369.

[29] Lugovaya T.S. Biometric human identification based on electrocardiogram. [Master's thesis] faculty of Computing Technologies and Informatics, Electrotechnical University "LETI", Saint-Petersburg, Russian Federation; June 2005.

[30] Goldberger, A., L. Amaral, L. Glass, J. Hausdorff, P. C. Ivanov, R. Mark, J. E. Mietus, G. B. Moody, C. K. Peng, and H. E. Stanley. "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220." (2000).