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Designing A Novel Biometric Authentication System Based on ECG Signals Using Deep Learning

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ABSTRACT

Biometric authentication systems play a crucial role in securing sensitive information and resources. This paper proposes a novel approach to biometric authentication by leveraging Electrocardiogram (ECG) signals. The proposed system employs a comprehensive methodology that includes signal processing, feature extraction, wavelet decomposition; QRS wave detection, internal calculation, wave modelling, distance and deviation calculation, averaging threshold, and an Artificial Neural Network (ANN) classifier. The entire system is implemented and evaluated using the MATLAB tool. The process begins with the acquisition of input ECG signals, followed by pre-processing to enhance signal quality. Feature extraction is then performed to capture the unique characteristics of the ECG waveform. Wavelet decomposition is employed to analyse the signal in both time and frequency domains. QRS wave detection identifies the specific components crucial for biometric authentication. Internally, the system calculates various parameters and models the ECG waves to establish a robust representation. Distance and deviation calculations further refine the feature set. An averaging threshold is applied to enhance the system's resilience to noise and variability. The final classification is accomplished through an ANN classifier trained on the extracted features. The proposed system outputs the authentication result, displaying whether the individual is identified as female or male. The system's performance is evaluated through extensive testing using a dataset of ECG signals. Results indicate high accuracy, demonstrating the effectiveness of the proposed biometric authentication system. This research contributes to the field of biometrics by introducing a novel approach based on ECG signals, offering a secure and reliable means of personal identification. The integration of deep learning techniques enhances the system's ability to adapt to variations in ECG patterns, making it suitable for real-world applications in security and access control.

Keywords: Deep learning, ECG Signal, ANN Classifier, Security, Biometric Authentication

I. INTRODUCTION

Biometric authentication systems have become integral in ensuring secure access to sensitive information and resources. The use of physiological signals, such as Electrocardiogram (ECG) signals, for biometric identification has gained attention due to the uniqueness and stability of these signals. ECG signals, which represent the electrical activity of the heart, exhibit distinct patterns that can be utilized for individual recognition. This paper introduces a novel approach to biometric authentication, focusing on the design and implementation of a system based on ECG signals using deep learning techniques.

The proposed system aims to enhance the reliability and security of biometric authentication by leveraging the intricate details present in ECG waveforms. Deep learning methodologies, particularly Artificial Neural Networks (ANNs), are employed to extract and learn complex features from ECG signals, enabling accurate and robust identification of individuals. This research addresses the limitations of existing biometric systems and contributes to the advancement of secure access control mechanisms.

Today, life engages technology in multiple ways, thus authentication in human technologies is very important. Secure and reliable authentication is in high demand. However, traditional methods for authentication such as face recognition, voice recognition and passwords are now outdated because faces are available in social media and couldn't differentiate between two twins, and voices can be easily recorded from calls. However, ECG signal is a universal characteristic [1]. The Electrocardiogram (ECG) is the recording of electrical activity of human heart using electrodes placed on the skin over a period of time. The shape of the waveform reveals the current state of the heart and it offers helpful information regarding the rhythm and function of the heart. There are 3 main components to an ECG: P wave, QRS complex and T wave [2]. Recently, the possibility of using this ECG signal as a biometric tool has been suggested because the composition and activity of the human heart is unique, stable, easy to collect, have a high performance and it's socially accepted. Its validity is well supported by the fact that both the physiological and geometrical differences of the heart under different subjects reveal certain uniqueness in the signal characteristics due to existing differences in morphology among individuals.

ECG signal gives information about the human heart, generally evaluated by an electrocardiograph. The various sensor placement combinations give little changes which enables improved particular portion of the waveform. 12 leads are the general usage of the health, which are categorized as chest and limb leads. All these evaluations consist normal behaviour as recurrent and as periodic patterns [11]. The QRS complex, which is made up of the waveforms Q, R, and S, is the most important part of the ECG. As it is covered by P and T waves, as shown in figure 1, it is typically elaborated to P-QRS-T.

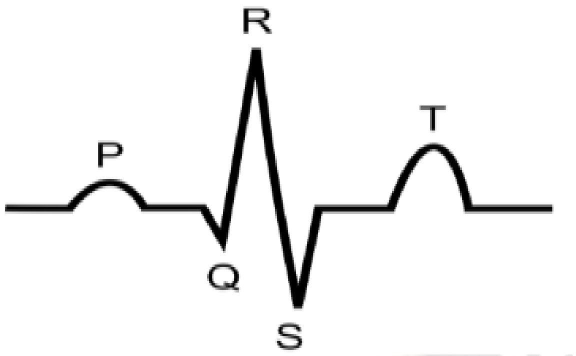


Figure 1. Normal Sinus Rhythm waveform and some of its relevant point

creating the individual identification these signals are appear in inter-individual variability [12]. Additionally, it is confirmed that day-by-day variability and long-term in addition, it has been proven that the long-term intra-individual variability are comparable [13], enabling the comparison among various periods, also considering confirmation with more than a year of separation [14].Additionally, from each and every life being ECG can be obtained which gives life proof identification. The signals from the ECG are involuntary, real its function cannot be cannot be accessed in easy way these signals which are representing the action of the organ. ECG is more popular and highly significant with these features in the field of biometrics and many studies have been under taken since before 2000s.

The organizational framework of this study divides the research work in the different sections. The Literature survey is presented in section 2. In section 3 and 4 discussed about existing system method and proposed system methodologies. Further, in section 5 shown Results is discussed and. Conclusion and future work are presented by last sections 6.

II. LITERATURE SURVEY

H. Silvaet. Silvaet. Al.[1] "Medical data safety and biometric configuration centered on ECG signals" definition based authorization is particularly important for areas whereby information security is necessary, such as Healthcare Information Systems (HIS), where even the safety of patient records as well as the track - and - trace of medical activities are absolutely critical. Insurance and patient history verification are fundamental. Current practices of addressing the issue involve biometric approaches, in every scenario, traditional methods allow only temporary verification; readers are usually settled in a fixed area, which involves direct interaction or proximity. In Healthcare Information Systems (HIS), comprehensive patient and care provider authentication is actually an problem that poses deficiencies and decreases the standard of treatment due to malfunctions due to misre cognizable data from government departments and organizations around the world have begun to recur to biometric approaches as a means of enhancing existing practices; nevertheless, conventional biometric systems still have several drawbacks.

M. M. Tawfiket, sir. Al. [2] "Human identification using the QT signal and the QRS complex of the ECG" This study assesses the possibility to use the ECG signal as a biometric feature for the human identification. The testing data of 550 lead I ECG tends to follow measured from 22 sound members in several circumstances used to authorize the structure. The proposed scheme removes special sections of the ECG signal from QRS complex to an end of the T wave. A development plan was carried out in this paper mostly on accomplishment of the use of ECG Electronic as part of the Biometric feature, a data set of 22 healthy individuals consists of a wide range of heart rate characteristics and three strategies were developed for permission., the analysis shows that its cardiac fluctuation does have a real effect on the protection of ECG signal as a biometric function which has been handled with 2 methods. The QRS complex of the ECG signal is shown to be reliable over the heart rate as well as beneficial for the single use as a Biometric involves.

Y. Ho, Wang et. Al. [3] "Study of Human Electrocardiogram for Biometric Recognition" Biometric Identification is confirmed by the identification of of person in terms of biological and physical signal features. This work presented and evaluates a further method for configured research of the singular-lead ECG for human recognition. Just after pre-preparing phase, the ECG flow is divided into multiple structures in which each window involves a single sound of ECG signal. Since successful QRS identification, specific temporal, amplitude and AR coefficients are derived and used as a contributor to the classification, recognizing the final aim of distinguishing individuals. Research work provides a biometric system for the structured study of a particular electrocardiogram of lead (ECG) of human authentication. The initial stage of such a system consists of a wide band-pass filter that used to noise removal as well as other artefacts produced from raw ECG signal.

A. Krishnapuramet. Al. [4] "Bayesian Method to Combined Feature Selection and Classifier Design" This article offers a Bayesian approach to know at that given period both an optimized nonlinear classifier including a subset of predictor factors that become the more efficient nonlinear classifier also a set of predictor factors that is more relevant to their classification function. The method uses high-profile importance to encourage sparsity in use of both theory capabilities and modules; such prior convictions assume the shape of regularizations for the possibility research which awards considerable clarity in the planning of knowledge. Researchers derive an expectation-maximization (EM) algorithm to effectively calculate the maximum a posteriori (MAP) point estimation of a various variables. The algorithm is applied of the latest public-of-the-art sparse Bayesian classifiers that, in effect, are seen as Bayesian equivalents of support vector machines. T. Jebaraet, man.

Al. [5] "Multi-task and kernel selection for SVMs" has registered a complex choice of components or, on other side, part determination for various support vector machines (SVMs) trained on distinct but inter-related datasets. A technique that is beneficial if several Electronic classification methods and individually marked datasets occur against even a shared input space. Distinguishable datasets will typically reinforce the traditional choice of portraits or greatly strengthen with the classification techniques. A multi-task recognition learning technique using the very extreme entropy segregation formula is identified. The consequent convex algorithms retain the global solution objectives of support vector machines. Even then, in relation to several SVM classification and regression parameters, they often collectively calculate an optimum set of attributes and an optimal kernel combination. Tests are seen in simplified datasets.

A. Bakkeret, guy. Al. [6] "Task clustering and gating for Bayesian multitask learning" Modelling a series of related regression tasks could be enhanced by making the activities "learn from one another" workable. In machine learning, this topic is tackled via multitask learning, whereby concurrent activities are modelled as inputs and outputs of the very same network. This is often achieved by a linear mixed-effects model where there is a distinction between 'set effects, which are the same for all tasks,' and 'random effects, which can differ among tasks. In this paper, we will follow a Bayesian method in that few of the parameters are distributed (the same across all tasks) and few are very closely linked across a common probability distributions which can be derived from results. e Throughout this manner, they try to incorporate the better aspects of both multi-level statistical approach as well as the neural network machinery.

R. Hoekemaet. al. [7] “Geometrical dimensions of the differences of multi-lead ECG recordings. Electrocardiogram (ECG) is used as a clinical tool for evaluating or assistance a diagnosis in a cardiac patient ever since it was recorded in a man by Waller and then enhanced by Einthoven. The electrocardiogram

(ECG) as assessed by healthy subjects reveals major inter-individual variations. Such variability is caused by geometric and physical elements. The comparative contribution of geometric components is evaluated in this analysis. What was more, the method used to correct such factors is described. This article demonstrates that since a huge portion of the ECG's variation should be directly linked to the geometric factor indicating the electrical density transverse processes of the thorax.

III. EXISTING METHOD

While existing literature demonstrates progress in ECG-based biometric authentication, there remains room for improvement. Current systems may face challenges such as susceptibility to noise, limited adaptability to individual variations, and the need for more sophisticated feature extraction methods. The proposed system aims to address these limitations by incorporating deep learning techniques, providing a more robust and accurate authentication mechanism.

IV. PROPOSED METHOD

The proposed system integrates signal processing, feature extraction, wavelet decomposition, and an Artificial Neural Network (ANN) classifier to create a comprehensive biometric authentication framework. This approach harnesses the power of deep learning to learn intricate patterns within ECG signals, enhancing the system's adaptability and accuracy. The internal calculation and modelling of ECG waves contribute to a more nuanced representation, while the averaging threshold ensures resilience to noise.

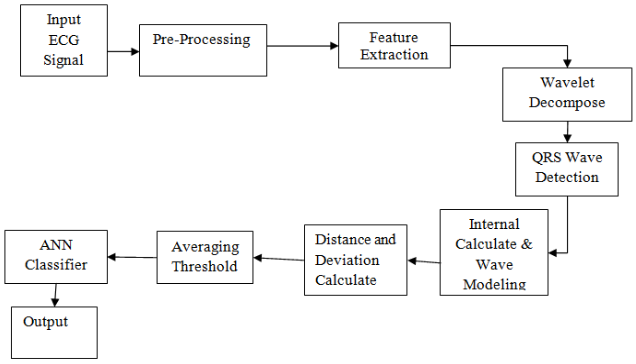


Figure 2. Proposed block diagram

In proposed System introduces a framework for how to appropriately adapt and adjust Deep learning techniques used to construct electrocardiogram (ECG)-based biometric authentication schemes. The proposed framework can help investigators and developers on ECG-based biometric authentication mechanisms define the boundaries of required datasets and get training data with good quality. To determine the boundaries of datasets, use case analysis is adopted. Based on various application scenarios on ECG-based authentication, three distinct use cases (or authentication categories) are developed.

A.MATERIALS AND METHODS

1. Data Acquisition

The ECG data used in this research is obtained from real experimental data. The subjects are 6 men aged 30-35 years and 2 women aged 30-35 years. The ECGs were recorded via a commercial ECG device. The number of recordings for each person is obtain from ECG lead 1. In this step signal is being acquired and stored in database, which is further used by system for identification purposes.

2. Pre-Processing

The first step is to apply a median filter to the input ECG signal in order to remove any noise and artifacts that may be present in the signal. This step will help to improve the accuracy of the subsequent processing steps.

3. Feature Extraction

The next step is to extract relevant features from the pre-processed ECG signal. This involves extracting the P-wave, QRS complex, and T-wave from the ECG signals. These features can be used to distinguish one ECG signal from another.

4. Wavelet Decomposition

Wavelet decomposition is used to decompose the ECG signal into different frequency bands. This can help to identify specific features of the ECG signal that are relevant for authentication.

5. QRS Wave Detection

The QRS wave is the most important feature of the ECG signal for authentication. QRS wave detection involves identifying the onset and offset of the QRS complex in the ECG signal.

6. Internal Calculate & Wave Modeling

Once the QRS complex has been detected, internal calculation and wave modeling can be used to extract additional features from the ECG signal. This step involves using mathematical models to analyze the shape and amplitude of the QRS complex.

7. Distance and Deviation Calculate

Distance and deviation calculation involves calculating the distance and deviation between the features of the ECG signal and a reference template. This step can be used to determine whether the ECG signal matches the reference template.

8. Averaging Threshold

The averaging threshold is used to determine whether the ECG signal is authentic or not. This threshold is calculated by averaging the distances and deviations of a set of training samples.

9. ANN Classifier

An artificial neural network (ANN) classifier can be used to classify the ECG signal based on its features. The ANN classifier can be trained on a set of known ECG signals to recognize patterns in the signals.

10. Output

The final output of the biometric authentication system is a binary decision indicating whether the input ECG signal is authentic or not. This decision is based on the results of the averaging threshold and the ANN classifier.

B. METHODOLOGY

Figure 4 depicts the block diagram of the proposed approach. It consists of pre trained ANN classifier for the performance evaluation of ECG signal classification for person authentication.

In the proposed methodology the steps as follows:

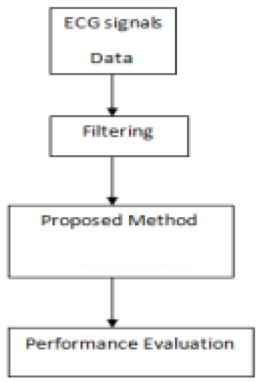


Figure 3. Proposed Methodology

- ECG signals are collected from database.
- ECG signals are filtered to remove high frequency noises.
- The signal pre-processing is done for removing the noise that is present in the gathered signals.
- Here, the pre-processing of the input signals is done by the BPF technique.
- A BPF represents a filter that passes signals using a frequency lesser than a chosen cut-off frequency and attenuates signals having frequencies more than the cut-off frequency.
- The layers of are concatenated with ANN classifier except the first and the last three layers.

V. SIMULATION RESULTS

This figure represents the raw ECG signal acquired from the individual. The ECG signal typically consists of P, Q, R, S, and T waves, each corresponding to different phases of the cardiac cycle. The irregularities and unique patterns in this signal form the basis for biometric authentication.

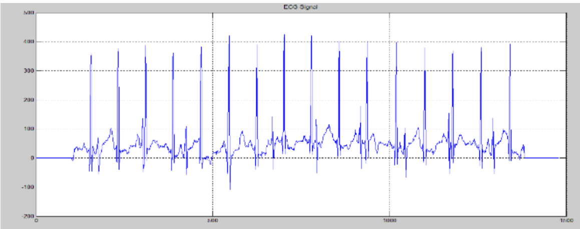


Figure 4: Input ECG Signal

The ECG signal is often contaminated by various types of noise during acquisition. Figure 5 displays the ECG signal after applying a Band pass Filter (BPF) to remove unwanted noise. This step is crucial to enhance the quality and accuracy of subsequent signal processing and analysis.

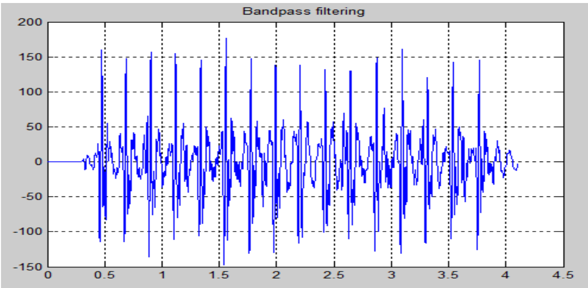


Figure 5: Noise removed signal via BPF

PQRS points represent the key landmarks in the ECG signal, namely the P-wave, QRS complex, and T-wave. This figure illustrates the identified PQRS points, providing a visual representation of the critical features used for subsequent analysis and feature extraction.

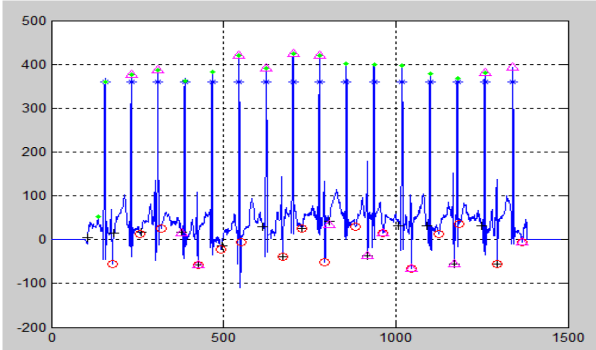


Figure 6: PQRS points representation

R-peaks are significant points within the QRS complex, and their accurate detection is vital for further analysis. Figure 7 shows the specifically detected R-peaks in the ECG signal, which serve as a foundation for subsequent processing steps.

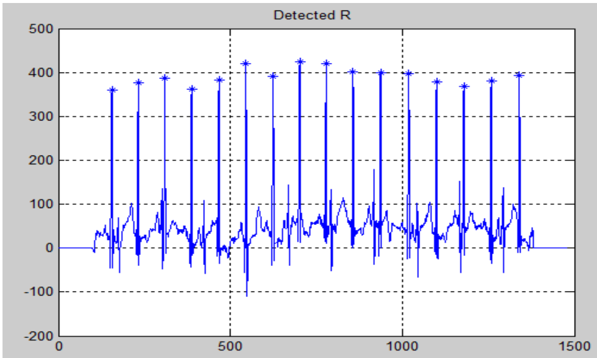


Figure 7: Detected R in ECG Signal

To mitigate the impact of noise and irregularities, a smoothing process is applied to the ECG signal. Figure 8 presents the signal after smoothing, providing a clearer representation of the underlying cardiac activity.

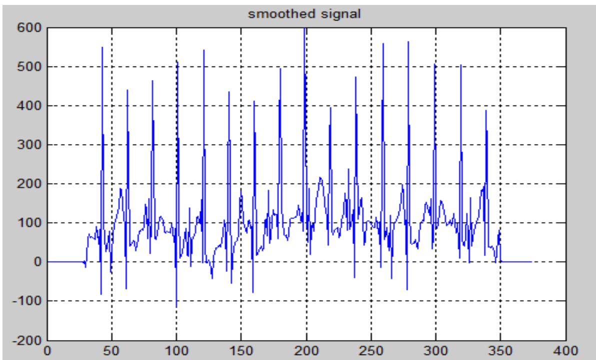


Figure 8: Smoothed Signal

Wavelet decomposition is utilized to analyse the ECG signal in both time and frequency domains. Figure 9 displays the ECG signal reconstructed at the 4th level of wavelet decomposition. This process enhances the system's ability to capture intricate details and features.

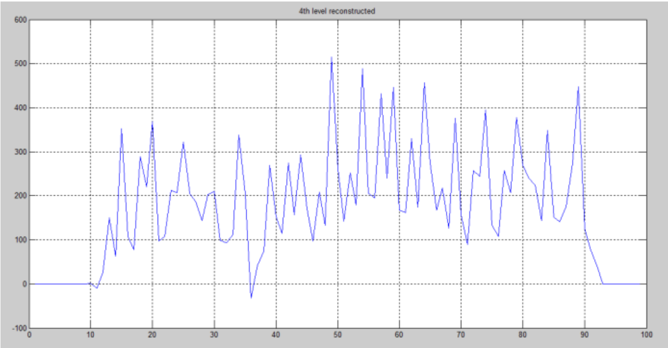


Figure 9: 4th level reconstructed

Similar to Figure 9, Figure 10 represents the ECG signal reconstructed at the 3rd level of wavelet decomposition. Multiple levels of decomposition allow for a more comprehensive analysis and extraction of features from different frequency bands.

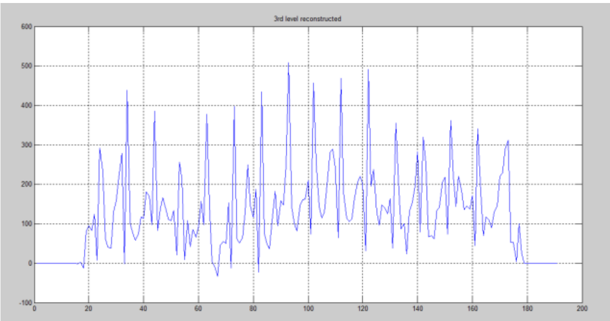


Figure 10: 3rd level reconstructed

After the pre-processing and feature extraction stages, the system utilizes an Artificial Neural Network (ANN) classifier to make a gender-based identification. Figure 11 illustrates the ECG signal classified as belonging to a male person. This final output represents the outcome of the biometric authentication process, indicating the system's determination of the individual's gender based on the unique features extracted from the ECG signal.

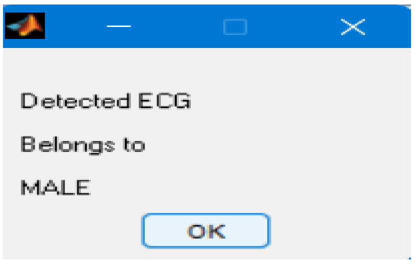


Figure 11: detected ECG Signal for male person

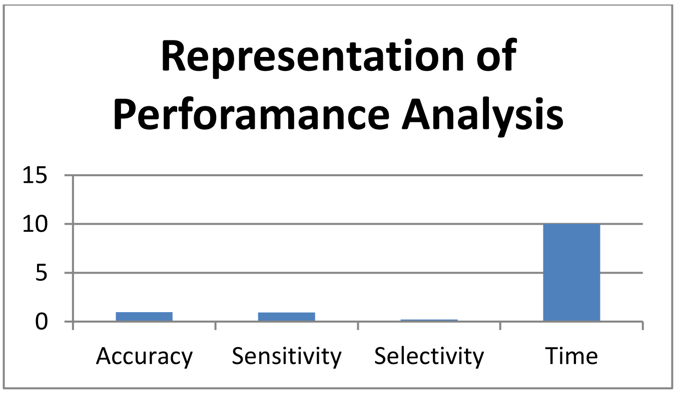
These simulation results collectively demonstrate the various stages involved in processing and analysing ECG signals for biometric authentication, emphasizing the importance of accurate detection and representation of key features in the signal.

PERFORMANCE ANALYSIS TABLE

TABLE I
OVERALL PERFORMANCE ANALYSIS

S. No	Performance Measures for proposed Method	Value
1	Accuracy	0.98
2	Sensitivity	0.95
3	Selectivity	0.2
4	Time	10 sec

PERFORMANCE GRAPH



The accuracy of the proposed method is 98%, indicating the percentage of correct classifications made by the system. This high accuracy suggests that the system effectively distinguishes between male and female individuals based on ECG signals.

Sensitivity, also known as True Positive Rate or Recall, measures the proportion of actual positive instances correctly identified by the system. A sensitivity value of 0.95 (95%) indicates that the system successfully identified 95% of the male individuals, demonstrating its ability to detect positive instances accurately.

Selectivity, also known as True Negative Rate, measures the proportion of actual negative instances correctly identified by the system. A selectivity value of 0.2 (20%) suggests that the system has a lower performance in correctly identifying negative instances (i.e., female individuals). This could be an area for improvement, depending on the specific requirements of the application.

The time parameter indicates the computational efficiency of the proposed method. With a processing time of 10 seconds, the system demonstrates relatively quick performance, making it suitable for real-time applications. However, the specific application context and requirements may influence whether this processing time is acceptable.

The high accuracy and sensitivity values indicate the effectiveness of the proposed biometric authentication system based on ECG signals. However, the lower selectivity value suggests that there is room for improvement in correctly identifying negative instances. Additionally, the processing time of 10 seconds aligns with real-time application requirements in many scenarios.

VI. CONCLUSION AND FUTURE SCOPE

This paper introduces a novel biometric authentication system that leverages ECG signals and deep learning techniques. The literature survey highlights the advancements and challenges in existing research, providing a foundation for the proposed system. The integration of deep learning aims to overcome limitations in current systems, offering a more robust and accurate approach to ECG-based biometric authentication.

FUTURE SCOPE

The future scope of this research involves further refinement of the proposed system, incorporating additional datasets for validation and testing. Exploring real-world applications and scalability is essential for practical implementation. Additionally, ongoing advancements in deep learning and signal processing techniques may open avenues for enhancing the system's performance and expanding its applicability in various security and access control scenarios. Continuous research in this domain is crucial for staying at the forefront of biometric authentication technology.

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