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Rhythmic Recognition: Harnessing Deep Learning for Cutting-Edge ECG Biometric Authentication

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Abstract:

Machine learning (ML) and deep learning (DL) are essential for analysing physiological signals, such as electrocardiograms (ECG), which can be continuously collected without requiring specific user engagement. Deep and machine learning demonstrate the ability to process large volumes of complex data with minimal human intervention, thereby contributing to their popularity in the health care sector. Electrocardiograms (ECG) represent a contemporary method of biometric verification closely linked to the distinctive characteristics of an individual's heartbeats. This study presents a convolutional neural network (CNN) model aimed at enhancing the efficiency and usability of user authentication processes. The proposed model demonstrates high accuracy and has undergone pretraining for classification across various disciplines. This was utilized for the authentication procedure following specific structural modifications. The proposed model generates an output suitable for patient authentication that is subsequently stored in a database. The model generates the patient's output upon the registration of a new patient. This output was subsequently utilized to compute the Euclidean Distance between the current patient's output and previous outputs stored in the database, resulting in a similarity score. Convolutional Neural Networks (CNNs) have been employed to design classification models that determine the electrocardiogram (ECG) corresponding to a specific individual based on a combination of feature sets produced during the transformation phase. The results indicate that, when adequate data are available for training, deep neural networks (DNNs) can achieve greater accuracy than many alternative methods.

Keywords: Machine learning, CNN-based model, Electrocardiogram, Deep learning

1. Introduction

Recent years have demonstrated a significant potential for biometric authentication across various sectors [1]. Physiological signals such as electrocardiograms (ECG) can be continuously acquired in the background without requiring specific user actions owing to advancements in Deep Learning (DL) and Machine Learning (ML) wearable devices for data collection. Electrocardiography (ECG) is a crucial tool for the diagnosis of cardiovascular disease (CVD), the leading cause of death worldwide. Cardiovascular disease is a prevalent condition that poses a significant threat to human health, particularly to the elderly population. This condition is characterized by disability, significant dominance, and elevated mortality rates. The global population is increasing. [1] The increase in cardiovascular disease (CVD) has emerged as a significant public health issue. ECG examination is an effective method for assessing cardiac status. Cardiovascular diseases require the classification and identification of ECG signals. Therefore, it is essential to classify linked ECG signals. The transition of ECGs from log to digital formats has increased the importance of automated computer analyses of

12-lead ECGs in medical diagnostics. The limited efficacy of classical algorithms restricts their utility as independent diagnostic tools, and relegates them to supportive roles. [1],[2]

Biosensors designed for placement on, within, and around the patient's body enable the continuous monitoring of physiological parameters during physical activity. Examples of physiological parameters include the blood oxygen level, heart rate, and core body temperature. Electrical bio signals, including electrocardiograms, electroencephalograms, and electromyograms (EMG), are widely recognized. The e-Health Cloud is a widely recognized cloud-based healthcare platform designed for efficient capture, storage, and management of substantial volumes of healthcare data. An untrustworthy cloud service provider may compromise the integrity of data and potentially initiate internal attacks. Data source networks are susceptible to external attacks. An attacker can potentially gain access to the network and healthcare equipment, allowing for the manipulation of patient bio signal data or creation of fraudulent data. Businesses, including insurance service providers, benefit from internal and external factors. [3] The personal information is a significant issue that warrants careful attention. Therefore, in addition to authenticating the patient, we ensured the security of the patient’s data by applying the established reversible data-hiding techniques. We conducted a thorough review of the various medical data-securing techniques proposed in the past and identified the most effective approach. After categorizing these approaches, we classified them into three distinct categories, cryptography, steganography, and watermarking, all of which are used in medical and health systems. Recently, several reversible methods of data masking have been reported. In certain instances, they rely on lossless compression technology to optimize space utilization. Among the available reversible data-concealing strategies, the difference expansion is the most efficient. Advancements in Artificial Intelligence (AI) technology, machine learning, and deep learning are being utilized to detect ECG signal features, with the aim of addressing challenges such as the substantial volume of ECG signal features and the significant manual workload involved. DL has gained significant traction over the past decade as a form of data-driven modelling that identifies patterns in data and makes accurate predictions. The integration of human voice to execute commands on smartphones, along with the hyper-personalization of advertisements, has profoundly influenced various aspects of contemporary life. In the medical field, deep learning has been used to identify melanomas from images of skin lesions, predict diabetic retinopathy from fundoscopic images, and segment the ventricle using cardiac MRI. The latter recently received FDA approval.[1], [2], [4], [5].

Deep neural networks (DNNs) have demonstrated remarkable performance in areas such as speech recognition and image classification, and there is significant optimism regarding the potential of this technology to enhance clinical practice and healthcare. Currently, the most effective system utilizes supervised learning to automate the examination diagnosis process. In the exploration of retinal infections and the analysis of breast cancer using 3-D optical coherence tomography images, the supervised learning technique, which maps input to output based on sample input-output pairings, demonstrated superior performance compared to a human specialist in their standard workflow. DNNs require substantial quantities of labelled data and present various challenges for medical applications. The volume of health data gathered from genetic sequences, electronic health records, and digital health wearables is substantial, making it challenging to analyse without the application of AI, deep learning, or artificial neural networks [6–8]. In various areas, such as fraud detection, supply chain management, agriculture, security, quality control, and sales prediction, machine learning (ML), deep learning, and artificial intelligence (AI) have shown the capability to convert vast amounts of unstructured data into actionable insights. Deep learning is a sub-discipline of machine learning. As the use of machine learning methods for health-related issues continues to increase, we can envision a future in which analysis, data, and innovation collaborate to support individuals without compromising their information. Currently, machine-learning-based appliances that incorporate real-time patient records from various healthcare organizations across multiple countries are becoming standard, enhancing the effectiveness of previously inaccessible treatment options [9, 10]. AI is the development of a system that emulates human cognitive processes, enabling the analysis of natural language and strategizing, perceiving, and navigating information to facilitate decision making with minimal human involvement. Machine and deep- learning techniques have been used in the field of Artificial Intelligence. Numerous small businesses, individuals, government entities, and organizations utilize machine learning and deep learning to analyse complex and varied data, aiming to achieve multiple objectives such as enhancing profitability, predicting sales, reducing production costs, and optimizing supply chain management. AL, ML, and DL have been identified as significant contributors to healthcare data management, as demonstrated in the classification of ML, AL, and DL. [11], [12], [13], [14].

2. Literature review

Machine learning (ML) and deep learning networks (DLN) have made significant progress in recent years, not only in voice recognition and image processing, but also in the detection of heart conditions based on ECG readings.

Reference [11] recently published a compelling investigation of the application of DNNs in ECG research. When trained on publicly accessible datasets, deep neural networks have the potential to achieve a performance comparable to state-of-the-art techniques for single-lead ECGs, and with an adequately sized training dataset, they may surpass the capabilities of practicing cardiologists. Nonetheless, as indicated by the authors, it remains uncertain whether this technology is effective in practical scenarios; 12-lead ECGs are the standard method [11].

The S12L-ECG (short-duration, standard, 12-lead electrocardiogram) is the most frequently utilized supplementary examination for assessing cardiac function and is applicable across various clinical environments, from primary care facilities to intensive care units. While monitoring cardiac activity, such as through the Holter test, which emphasizes cardiac rhythm, the S12L-ECG provides a thorough evaluation of the electrical activity of the heart. Examples include conduction abnormalities, arrhythmias, cardiac chamber hypertrophy, acute coronary enlargement, medications and electrolyte disorders. A DL method that enables a precise S12L-ECG analysis would yield significant benefits. S12L-ECGs are often conducted in environments that lack qualified personnel to assess and interpret ECG tracings, including primary care facilities and emergency departments. The interpretation of S12-ECGs reveals that primary facilities and emergency department health providers exhibit limited diagnostic capabilities [12, 13].

Pawiak and Acharya (2020) employed a deep genetic ensemble of classifiers to classify long-duration ECG signals (10 seconds). Gao et al. (2019) employed an efficient long short-term memory (LSTM) recurrent network model to classify eight distinct heartbeat types. To classify five distinct heartbeats, [16] proposed an optimization-driven deep convolutional neural network (CNN). Unlike conventional neural networks, they can automatically extract features, identify intricate data patterns, and eliminate the need for complex signal preparations. Deep learning networks exhibit enhanced nonlinear fitting capabilities, enabling them to recognize single-lead, multiclass, and imbalanced ECG datasets more effectively [17].

A CNN is a feedforward neural network that has been widely employed in deep learning for the classification of arrhythmia ECG signals. Most previous studies [16, 17, 18] have focused on the identification of five main macro groups: ventricular ectopic (V), non-ectopic (N), fusion (F), supraventricular ectopic (S), and unknown (U) (Q).

Biel et al. [19] utilized fiducial points from a standard 12-lead ECG to delineate features, and applied this methodology for classification. Israel et al. [20] employed linear discriminant analysis (LDA) for classification purposes. A comparable methodology was employed by Wang et al. [21], who enhanced their research by applying a discrete cosine transform (DCT) to the autocorrelation function. Seachia [22] examined the efficacy of segmenting ECG heartbeats by applying Fourier coefficients, and Platanista [23] pioneered the proposal of an ECG biometric recognition approach that does not depend on waveform detection. This method employs DCT to minimize the dimensionality of ECGs by analyzing their autocorrelation. Agrafioti [24] employed the DCT and LDA to develop an autocorrelation template. To enhance calculation efficiency and minimize memory usage, Fatemian [25] utilized a reduced number of templates per subject and developed a tailored pulse template using Discrete Wavelet Transform Coefficients. Wubbeler et al. [27] and Shen et al. [26] employed template-matching methods to classify properties related to the QRS complex.

Various strategies have been introduced for ECG biometric systems that employ different ECG datasets [28]. The authors of [28] conducted a comparison of the averages related to categorization identification, equal error rates (EER), and authentication scenarios by analyzing pathological signals from ECG databases across multiple investigations. In the identification scenario, the weighted average rate was 94.95 percent, whereas in an authentication situation, the overall EER was 0.92 percent, based on their findings. The findings in [28] demonstrated that the number of ECG leads utilized influences the recognition performance, as does the selection of characteristics.

Deep learning algorithms have been applied to ECG biometrics in several recent studies []. A CNN was employed in this study to classify ECG heartbeats in the patients [29]. A residual CNN with an attention mechanism was developed for human authentication using an ECG in [30]. When analyzing one-dimensional signals such as ECG with sequential data, a recurrent neural network (RNN) provides advantages over convolutional neural networks (CNNs).

3. Methodology

- **Dataset**

The primary consideration prior to training any classification-based model is the data, which serves as an essential requirement for initiating the training of any machine-learning model. The data that are labelled and utilized for training an Artificial Intelligence model are referred to as the training data. Conversely, data that are new to the model and assist in evaluating its accuracy are known as testing data. In the process of training a CNN-based model for patient authentication using ECG records, An open-source dataset comprising 290 distinct patients and approximately 549 ECG records was employed to train a CNN-based model for patient authentication using ECG records. The data included the records of 209 male and 81 female patients, with ages ranging from 17 to 87 years. This analysis indicated that a comprehensive clinical report of 22 patients is not currently available. Therefore, we continued the analysis by using data from 268 patients in the proposed model. Figure 1 presents a comprehensive overview of the 268 patients.

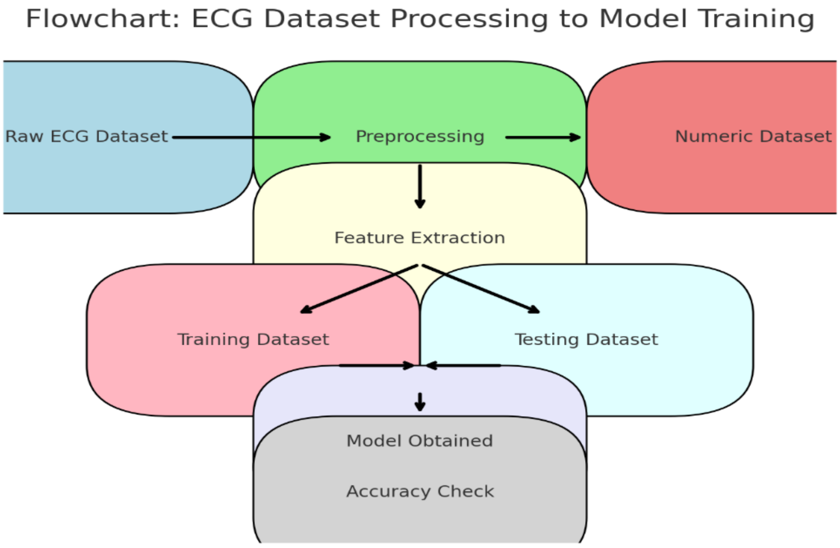


Fig. 1 Proposed ECG authentication predictive model

Table 1 Detailed patient description regarding diagnostic class

Diagnostic Class	**Number of Subjects**
Myocardial Infarction	148
Cardiomyopathy/Heart Failure	18
Bundle Branch Block	15
Dysrhythmia	14
Myocardial Hypertrophy	7
Valvular Heart Disease	6
Myocarditis	4
Miscellaneous	4
Healthy Controls	52

- **Implementation**

The implementation of a patient authentication mechanism utilizing deep learning through CNNs is examined in detail.

Baseline Model

A CNN-based model was established using the ECG dataset as the foundation. The proposed model has undergone pre-training for categorization across many subjects, and has a high degree of accuracy. We used this for the authentication procedure,, following structural modifications. Initially, we assumed that specific patients had been validated, and subsequently inputted their ECG signals into the model. The proposed model generates an output for patient authentication that is then stored in a database. Upon registration of a new patient, the model generates the patient's output, which is subsequently used to compute the Euclidean Distance between the current patient's output and the previous outputs recorded in the database as a similarity score. Ultimately, we evaluated the similarity score against a threshold value of 0.94 to determine if the new patient was successfully authenticated. The stages involved in the development of the basic system are outlined below:

BEGIN *// Step 1: Start the process*

Start // Step 2: Collect data

Data Collection   // Step 3: Gain insights from the collected data

Getting Data Insights   // Step 4: Pre-process the data

Pre-process Data   // Step 5: Extract and select important features

Feature Extraction and Selection   // Step 6: Split data into training and testing sets

Split Data into Train and Test Sets   // Step 7: Generate and train the model

Generate Model   // Step 8: Test the model

Test Model

IF model output is correct THEN   // Step 9: Finalize the model if output is satisfactory

Final Model

ELSE   // Step 10: If output is incorrect, go back to data pre-processing

Go to Pre-process Data

END IF   // Step 11: End the process

Stop

END

- **Data Preprocessing**

In the initial phase of model training, specifically during data pre-processing, we extracted various features from the raw dataset. An ECG signal contains multiple fiducial points, which can be used to segment a long signal into smaller sections. The signal underwent an initial resampling at a frequency of 200 Hz. Subsequently, we identified all of the 'R' points and selected a one-second time window for each of them. Consequently, we acquired a substantial quantity of 'QRS' combinations, each comprising 200 respondents. Approximately, 20 complexes were selected at various time intervals. Once all individual records have been pre-processed, the complexes can be utilized as training datasets for the CNN.

- **Creating Model**

The proposed model was developed using a convolutional neural network framework. We implemented the gradient descent algorithm to develop the convolutional neural network architecture over 20 epochs to optimize the network model and improve its efficiency. Each batch contained approximately 16 samples.

- **Authentication Procedure**

Convolution layers containing data pertinent to the ECG signal are stored in the database. Subsequently, the previously trained CNN-based structure was modified by eliminating the fully connected layers to achieve the high-dimensional characteristics of the ECG signals. Initially, it was determined that a registered patient had created an original database by utilizing their prior ECG signals. Upon receiving a new signup request, our model aligns it with the original database and calculates the mapping score by using the Euclidean Distance formula.

$$\boldsymbol{distance(a,b)} = \sqrt{(\boldsymbol{a_1}-\boldsymbol{b_1})^2+(\boldsymbol{a_2}-\boldsymbol{b_2})^2+\cdots+(\boldsymbol{a_n}-\boldsymbol{b_n})^2} \quad (1)$$

where ai is used to signify the values of high-dimensional traits of the patient data and bi is used to signify the comparable characteristics of the database. If distance(a, b) is greater than the threshold distance which is 0.94 in the proposed model, only the patient passes the authentication process and is granted access to the server; otherwise, the patient refuses.

- **Complexity Improvisation of the Model**

Because the different weight values in the convolution layers are floating-point integers, the CNN-based architecture offers outstanding accuracy values, but has tremendous complexity. Various floating-point computations are required to determine the output of a CNN model that relies on convolution calculations and has a major impact on performance values. To address this problem, we replaced the original weight values with the binary and approximate weight values.

- **Binary Weight Conversion**

In binary weighted approach we replaced original floating-point integers with binary digits (1 and -1). To carry out this transformation, we use the SIGN function:

$$\overline{W} = \left(\frac{1\ if\ w_i \geq 0}{-1\ if\ w_i < 0} \right) \quad (\mathbf{2})$$

Binary weights have fewer multiplication operations than the original weights and only require an inversion operation in the forward transmission.

- **Approximation Weight Conversion**

The original weight values were adjusted by using exponential numbers throughout the procedure. Without sacrificing generality, the floating-point number weight x can be expressed as x= p/2^n , where p is integer. Furthermore, any integer p can be expressed as the sum of a series of exponents (p = 2x + 2y+...), which can be converted into additional bit-shifting operations. The approximation extent is controlled by the hyperparameter n. The estimated weights were similar to the old weights, as n increased.

The accuracy score of the authentication process is essential for its application to the users. Consequently, we assessed the process accuracy of the architecture by using three threshold values. For the login check process, we arbitrarily split the dataset between intruders and users. We tracked the similarity scores of each login transaction. Later, we achieved complete precision, and for basis cleaned dataset training, it the model with an accuracy 98.22% and validation loss of 2.89 approx.

The accuracy score of the authentication process is essential for it to be put into user. As a result, we assessed the process's accuracy of the architecture on three different threshold values. For the process of login check, we arbitrarily split the dataset between intruders and users. We kept track of the similarity score for each login transaction. Later, we achieved complete precision and for basis cleaned dataset training makes it the model which has accuracy 98.22% and val_loss is 2.89 approx.

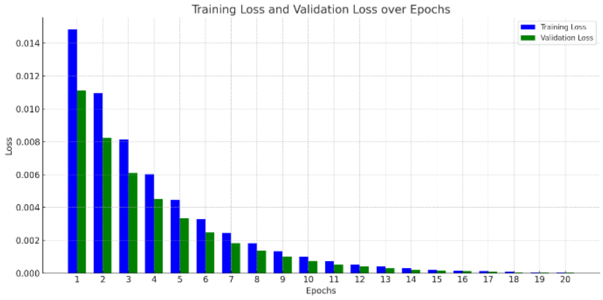
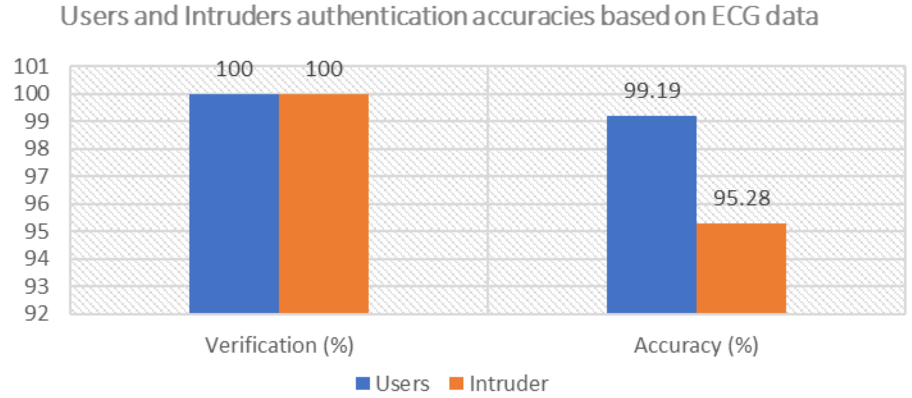


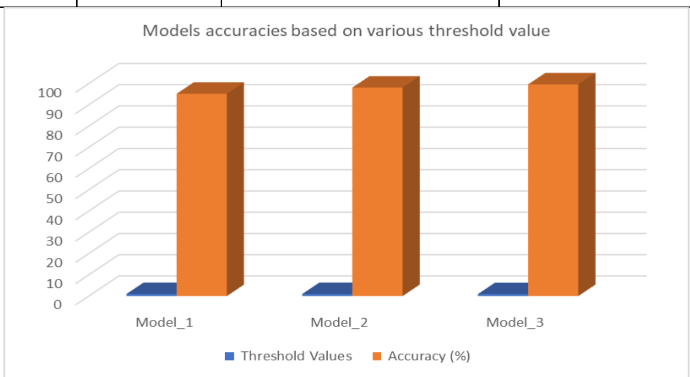
Fig. 3 Model training loss and validation loss

In this model, authors performed the epochs and initially losses are high however when epochs gradually increases, the training and validation losses decreases simultaneously.

S. No.	Models	Verification (%)	Accuracy (%)
1	Users	100	99.19
2	Intruder	100	95.28



S. No.	Models	Threshold Values	Accuracy (%)
1	Model_1	0.98	95.21
2	Model_2	0.96	98.11
3	Model_3	0.94	99.62



The accuracy value of the model on three different threshold values which are 0.94, 0.96, and 0.98 respectively for Model_3, Model_2, and Model_1. Thus, based on their threshold value Model_1, Model_2 and Model_3 are given average accuracy 95.21, 98.11 and 99.62% respectively on test datasets.

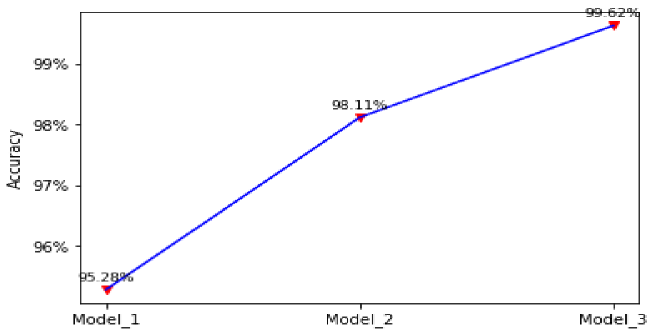


Fig. 4Visualization of Models Accuracies

Sample data inputs

Index	Label	Record	0	1	2
498	patient0O1	s0014Ire	0.199939	0.191823	0.214920
438	patient001	s0014Ire	0.199939	0.191823	0.214920
497	patient001	s0014ire	0.166484	0.203104	0.198691
448	patientO03	s0017Ire	0.708298	0.712344	0.735886
449	patient001	s0014Ire	0.166484	0.203104	0.198691
339	patient0O2	s0015ire	0.130575	0.035678	0.127130
466	patientOO3	s0017Ire	0.659788	0.656352	0.641516
372	patient002	s0015ire	0.213821	0.104104	0.181670
429	patient001	s0014Ire	0.204671	0.193204	0.226268
441	patientO03	s0017Ire	0.685253	0.728064	0.722454

Table 4 Performing testing authentication of patients, taking 10 sample data records

Records	Label	Accuracy
Record 1	Patient001	96.79
Record 2	Patient001	96.26
Record 3	Patient001	96.16
Record 4	Patient003	98.45
Record 5	Patient001	96.76
Record 6	Patient002	98.93
Record 7	Patient003	98.93
Record 8	Patient002	99.71
Record 9	Patient001	97.10
Record 10	Patient003	98.08

An authentication procedure was performed for various patient records. This section presents several example records from three distinct patients, as illustrated in Fig. 5 and listed in Table 4, based on sample inputs.

This study addresses this new model in the methodology section. To verify the validity of the patients, we implemented a new model based on their data, after removing their names and report numbers. The sample input yield values are listed in Table 4. The obtained values included several entries, with the final column of this table indicating the probability of being an authenticated patient.

4. Conclusion

This study proposed a CNN-based classification system for ECG signals constructed using an ECG dataset as the foundational framework. During the preprocessing phase, various attributes were extracted from the raw dataset. An ECG signal contains various fiducial points, which can segment a long signal into smaller sections. To optimize the network model and enhance its efficiency, we employed a gradient descent method to develop the convolutional neural network architecture over 20 epochs. To extract high-dimensional features from ECG signals, we stored the convolutional layers associated with ECG data in the database and subsequently modified the pretrained CNN architecture by removing the fully connected layers. Upon receiving a new signup request, our model correlates it with the original database, and computes a mapping score using the Euclidean Distance algorithm. Consequently, we assessed the accuracy of the architecture by using three different threshold values.

The dataset is randomly partitioned into invaders and users for login verification. We monitored the similarity scores of each login transaction. Subsequently, a complete precision was achieved.

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