EEG Biometric: Rapid Identification Across Varied Electrode Configurations and Limited Recording Times

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***Abstract*—The use of biometric recognition for identifying individuals has become common in modern security systems. However, the growing demand and usability of this technology have also increased the associated security risks. Therefore, it is necessary to find more reliable biometric traits than the ones currently in use. Recently, the brain signal captured using the electroencephalogram (EEG) technique has been identified as a promising biometric option due to its exceptional level of distinctiveness, consistency, and widespread application. This paper presents a novel approach to biometric identification utilising EEG data. The methodology employs a short-time Fourier transform (STFT) for feature extraction, followed by channel-wise division of the data. Subsequently, Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models are implemented individually for each channel. The final step involves the integration of these models using an ensemble voting classifier. Through this ensemble approach, the system shows significant improvements over baseline papers in performance metrics such as accuracy, precision, recall, and f1-score by combining the predictions from multiple models.**

***Index Terms*—EEG, biometric, authentication, ensemble learning for biometric.**

I. Introduction

Biometric identification systems are becoming an essential part of modern civic life and have many applications, ranging from unlocking the mobile phone to person identification for security surveillance applications, and so on. Facial recognition, fingerprint, and iris scanners are among the most widely used modern biometric systems. However, a person's exposure to the external environment makes these biometric traits vulnerable to spoofing attacks. Researchers are increasingly directing their attention towards cognitive biometric authentication, which relies on electroencephalograms (EEGs), as they cannot be easily falsified. EEG technology detects the electrical activity of brain waves by placing electrodes on the scalp [1]. These electrodes measure the synchronous activity of millions or even trillions of neurons with similar spatial orientation, providing valuable data on cognitive functions and neural reactions. EEG recordings are specific to individuals and cannot be replicated, and with the increasing use of wireless and portable headsets like the Epoc [2], EEG data collection and management have become easier. Recorded EEGs provide information about the brain's specific reactions to internal or external stimuli [3]. Event-related potentials (ERPs) are changes in the EEG that occur in response to various stimuli, such as visual or auditory stimuli [4], or during the brain's rest state.

In this paper, we work on identification using auditory-evoked potentials (AEPs) and visual-evoked potentials (VEPs). AEPs are neuroelectrical potentials generated by applying an auditory stimulus to the ear, while VEPS are the ones generated in response to some visual elements like images or videos. The AEPs and VEPs are stimulus-dependent, i.e., they change by varying the auditory and visual stimuli [5]. This adds an extra feature to the AEP and VEP signals over conventional biometrics and other biosignals, such that even if the AEP signal is breached or hacked, it can still be reused for biometric authentication by varying the respective stimulus. Biometric authentication utilising AEP and VEP signals can be advantageous in specialised applications such as telemedicine and situations where protective equipment is employed [6]. Advances in wearable technology and biomedical instrumentation have made it possible to conveniently and remotely record AEPs. Integrating the advanced biometric features into AEP/VEP will streamline the process of gathering data for mental health assessment while simultaneously identifying the patient using the same signal, eliminating the need for further data collection for identification purposes.

This paper has six sections. Section II covers related work. Section III details the data set, including stimuli, equipment, acquisition setting and protocol, and the proposed methodology. Section IV outlines the model's experimental setup. Section V analyzes the results, compares our work with previous studies, and offers additional discussion. Finally, Section VI summarizes the major conclusions.

II. Related Work

EEG has been extensively used in various medical practices like epilepsy diagnosis [7], emotion recognition [8], monitoring brain function [9], etc., highlighting its versatility and utility. Enhancing the robustness and reliability of identifying systems has been a focus of recent research in EEG-based biometric identification. Wang M et al. [10], for example, showed how deep learning models could capture complicated EEG patterns and hence considerably enhance recognition accuracy. In a similar vein, Rakhmatulin et al. [11] investigated the application of convolutional neural networks (CNNs) to EEG signal analysis and feature extraction. Zeynali et al. [12] investigated optimised electrode placement strategies, finding that a reduced set of strategically placed electrodes could still capture sufficient biometric information. Bakırcıoglu et al.[13] proposed the Convolutional Neural Network (CNN) approach for biometric identification and achieved a correct classification rate (CCR) of 72.71%. However, by utilising only 4 channels, the CCR improved to an average of 83.51%. Additionally, the training time was significantly reduced from 626 to 306 seconds. It demonstrates the effectiveness of CNN architectures in processing EEG data for biometric identification tasks.

Another research paper [14] investigated the performance of multi-channel and single-channel approaches using the BED dataset. The multi-channel approach achieved an impressive accuracy of 95%. On the other hand, the single-channel approach yielded training and testing accuracies of 98.27% and 97.13%, respectively. The study compares the efficacy of utilising multiple EEG channels versus focusing on individual channels for biometric identification. It demonstrates that both approaches can achieve high accuracy, with the single-channel approach exhibiting slightly superior performance [14]. Auditory stimuli have also been explored, though to a lesser extent, in the context of EEG-based authentication. The authors [15] investigated the use of auditory evoked potentials (AEPs) for user identification, demonstrating that specific sound patterns can elicit unique brainwave responses suitable for authentication.

III. Methodology

We have designed a comprehensive framework in our proposed methodology to effectively address the inherent challenges of variable electrode configuration and inconsistent data acquisition time periods in EEG-based biometric identification systems. Our main goal is to design a biometric identification system using EEG, irrespective of the number of electrodes used during data reading, and to keep the duration of data acquisition as short as 2 seconds for fast and efficient identification of subjects. Fig. 1 shows the entire architecture's workflow. Thus, the prepared methodology encompasses several key steps:

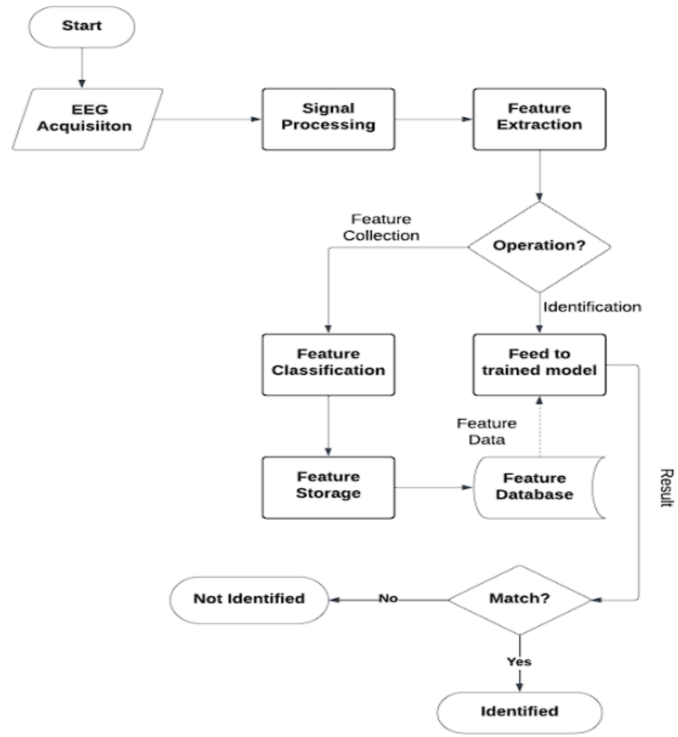

Fig. 1. Block diagram representing workflow of a biometric architecture

A. EEG Datasets

For our work, we utilise two publicly available datasets, namely the Auditory Evoked Potential EEG-Biometric dataset (AEP dataset) [16] and the Biometric EEG dataset (BED dataset) [17]. These datasets provide valuable EEG recordings obtained from human subjects under various experimental conditions.

- Auditory Evoked Potential (AEP) EEG-Biometric dataset:
  This dataset consists of over 240 two-minute EEG recordings from 20 volunteers, including both resting-state and auditory stimuli experiments. EEG signals were recorded using the 10/10 worldwide EEG system, with electrodes at specific locations such as T7, F8, Cz, and P4. Reference and ground electrodes were inserted in the left and right ears for calibration. The stimuli for data acquisition included three-minute sessions of resting-state with eyes open and closed, listening to songs in native and non-native languages, and listening to neutral music using both in-ear and bone-conducting headphones.
- Biometric EEG Dataset (BED):
  The BED dataset consists of EEG responses from 21 subjects to various stimuli across three chronologically

disjointed sessions. Stimuli presented to subjects include images designed to elicit specific emotions, mathematical computations (2-digit additions), resting-state conditions with eyes closed, and visual evoked potentials at different frequencies. EEG recordings are segmented, structured, and annotated according to the presented stimuli, facilitating analysis and interpretation. The dataset also includes features extracted from each EEG segment, as described in the associated publication.

B. Data Pre-processing

In this stage, the EEG data undergoes several preprocessing steps to enhance its quality and usability for subsequent analysis. A first-order Butterworth filter with cutoff frequencies between 1 Hz and 40 Hz is applied to remove noise and retain relevant frequency components. A notch filter at 50 Hz is employed to eliminate electrical interference, such as power line noise. The preprocessed data is divided into short time windows, typically around 2 seconds in duration. This segmentation aids in managing the data and allows for the analysis of temporal dynamics. These preprocessing steps are consistently applied to both the Auditory Evoked Potentials (AEP) and Biometric EEG Data (BED) datasets.

C. Feature Extraction

The Short-Time Fourier Transform (STFT)[18] is a time-frequency analysis technique used to extract features from EEG signals. The continuous EEG signal is divided into short, overlapping segments, often using a windowing function like the Hamming window. The Fourier transform is applied separately to each segment to analyse the frequency content over time. The magnitude of the resulting STFT coefficients is squared to obtain the spectrogram, a visual representation of frequency content versus time. Spectrograms provide insights into how the spectral characteristics of the EEG signals evolve over time. The equation of STFT is shown below.

$$S(m,k) := \sum_{n=0}^{N-1} x(n+mH)\omega(n)e^{(-i2\pi kn/N)} \tag{1}$$

where, K is the frequency index with respect to Nyquist frequency. N is the duration of the section. hop size (H), which is the step size of the window to be shifted. w be a sampling window function which is w: [0, N-1] $\rightarrow$R, m: [0, M] and M is the maximum frame index mathematically, M = (L-N)/H.

D. Channel Selection:

Channel selection involves choosing a subset of EEG channels for further analysis based on predefined criteria. The 10/10 worldwide EEG system was followed in our instance when choosing the electrode locations, which were T7, F8, Cz, and P4 [19-20]. The AEP dataset, however, had only these four electrodes as the original set of electrodes. It has been observed through multiple previous studies that these selected electrodes are more relevant for the identification task because they have a high signal-to-noise ratio (SNR) and minimal artefact contamination. For the BED dataset, we have done a comparative study between the model that incorporates all 14 available channels and the model that ingests data from selected 4 channels (drawing parallel from 4 channels of the AEP dataset) only in the result section of this paper. The four channels selected for BED are T7, F8, FC6, and P8[19-20] for the reasons mentioned above.

E. Individual Channel Processing:

In our methodology, each selected EEG channel undergoes a comprehensive processing pipeline to extract meaningful features and facilitate accurate biometric identification. The spectrogram features were split into training and testing sets with an 80-20 split, done randomly. The training phase of the utilise 80% of the total data and builds the model. While the remaining 20% of the data was tested on the trained model. The training workflow is shown in Fig. 2 and consists of the following steps:

CNN:

CNNs are adept at capturing these spatial dependencies through their convolutional layers, enabling them to learn discriminative features directly from the scalp electrode layout.The feature extracted through STFT represents a spectogram of the original EEG data. Spectrograms provide a concise 2D representation of EEG data, where one axis represents time and the other frequency. CNNs are naturally designed to handle 2D spatial data, making them well-suited for processing spectrograms directly.

LSTM:

LSTM networks are specifically designed to capture temporal dependencies and patterns in sequential data, making them well-suited for analysing EEG signals over time. By leveraging the memory cells and gating mechanisms of LSTM units, the network can effectively model the temporal dynamics present in EEG recordings, capturing subtle variations and patterns. Fig. 3 displays an LSTM cell.

Fully Connected Layers (Dense Layers):

The output of the LSTM layers is fed into two fully connected layers (also known as dense layers) for further feature extraction and representation. Fully connected layers enable the model to learn complex relationships between the extracted features, allowing for higher-level representations of the EEG data. These layers serve as intermediate steps between the LSTM-based temporal modelling and the final classification task, enabling the model to abstract relevant information from the EEG signals.

Softmax Layer:

The final layer of the processing pipeline is a softmax layer, responsible for generating class probabilities for each segment of EEG data. Softmax activation transforms the raw output of the network into probability distributions over the possible classes, facilitating interpretation and decision-making.

F. Ensemble Learning with Voting Classifier:

A voting classifier is an ensemble technique that generates a final prediction by aggregating the predictions of several separate classifiers. The obtained output of the models is fed as

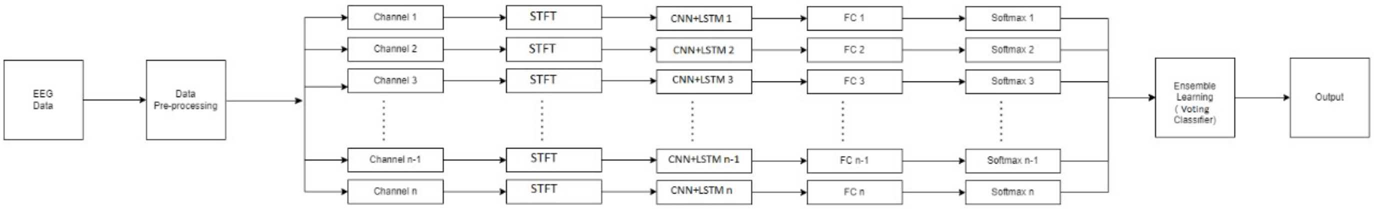

Fig. 2. Complete training workflow diagram of the model

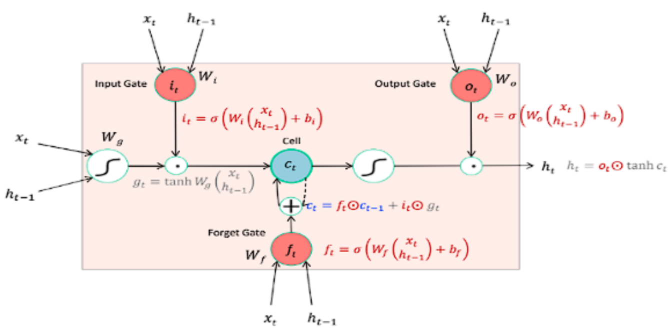

Fig. 3. Diagram of a LSTM cell.

input to a hard voting classifier, where the majority prediction is selected as the final prediction, with each classifier in the ensemble receiving a vote. However, we would like to make a small change in the classifier logic. We have added a condition for the classifier that if the support for a class is less than 75% i.e., there is no particular class that was predicted by 75% of the total models, then the test subject will be considered unidentified, which means the test subject is not authenticated. Fig. 4 displays the architecture of the voting classifier.

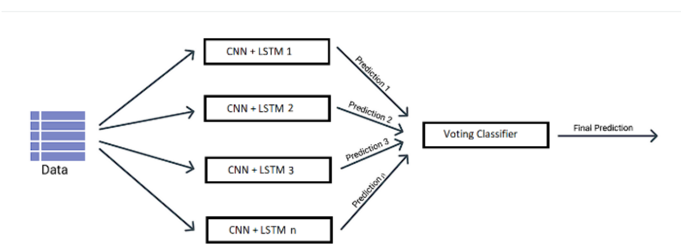

Fig. 4. Architecture of a voting classifier.

G. Output:

The output of the proposed methodology is a robust EEG-based biometric identification system capable of accurately identifying individuals within a short recording window. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the performance of the system. The model's effectiveness is validated across various electrode setups and recording durations to ensure its practicality and reliability in real-world scenarios. By meticulously following each step of this detailed methodology, we aim to create a sophisticated EEG-based biometric identification system that addresses existing limitations and delivers reliable performance in diverse settings.

IV. Experimental Setup

The training phase of our model starts with data being moulded into a consistent input shape, which is fed to the starting layer of our model. We have found two convolution layers, each followed by a max pooling layer, to be best performing for our case. We used the ReLu activation function and experimented with different strides convoluted with 3x3 filters. The output from this layer is subjected to a dropout layer for regularisation and to reduce the number of neurons. Thus, there are two LSTM layers, each accompanied by a dropout layer with a drop factor of 0.2, before being fed to fully connected layers. We have used two dense layers with 128 and 64 neurons at the end of all models, which get fed to the final softmax layer, which outputs an array of 20 dimensions representing the predicted output of each input, e.g., a signal. The training of the model has been optimised with the Adam optimizer, and the loss function is chosen as categorical crossentropy.

For the purpose of the experiment, an attention mechanism was incorporated into the architecture, right after LSTM, to dynamically weight the importance of different regions in the data. The attention mechanism allowed the model to focus on salient features in the EEG data, enhancing its discriminative power by giving more weight to relevant parts of the input. An attention model, in the context of neural networks, is a mechanism that allows the model to focus on specific parts of the input data, giving them more weight during processing. This mechanism is inspired by human attention, where certain elements in a scene or a piece of information are prioritised over others based on their relevance or importance to see if the mechanism that allows the model to focus on specific parts of the input data gives them more weight during processing.

V. Results and Discussion

In our first study, we utilised the Auditory Evoked Potential EEG-Biometric dataset for biometric identification purposes. Our suggested methodology's performance was compared to a baseline model that used a straightforward CNN+LSTM architecture that took in all channels simultaneously. Notably in Table I, the baseline model achieved an accuracy of 90%, as shown in the accuracy curve in Fig.5. Adding an attention

TABLE I
ACCURACY COMPARISON BETWEEN PRE-EXISTING MODELS VS OUR PROPOSED MODEL FOR (AEP DATASET)

Models	Accuracy
k Nearest Neighbours (KNN) [9]	60.3%
Multilayer perceptron (MLP) [9]	61.9%
eXtream Gradient Boosting (XGBoost) [9]	85.4%
CNN+LSTM	90%
CNN+LSTM with attention	89.1%
CNN+LSTM with Ensemble learning	98.0%

TABLE II
METRICS COMPARISON BETWEEN MODEL WITH ALL CHANNELS TAKEN AT ONCE VS ENSEMBLE OF CHANNEL INDEPENDENT MODELS (AEP DATASET)

Metrics	All channels	Individual(ensemble)
Accuracy	0.905	0.980
Precision	0.896	0.995
Recall	0.900	0.988
F1 score	0.892	0.992

model on top of that model didn't exceed the accuracy, as it could only be accurate 89.1% of the time. However, our method, which leveraged individual channel processing and ensemble learning, demonstrated a significantly higher accuracy of 98%. This substantial improvement underscores the efficacy of our approach in enhancing biometric identification accuracy. Through the use of hard voting, the ensemble learning technique aggregated predictions from several models trained on different channels, enabling robust decision-making. This allowed us to achieve better performance than the baseline model by utilising the distinct information that each channel captured. More performance metrics have been compared and listed in Table II.

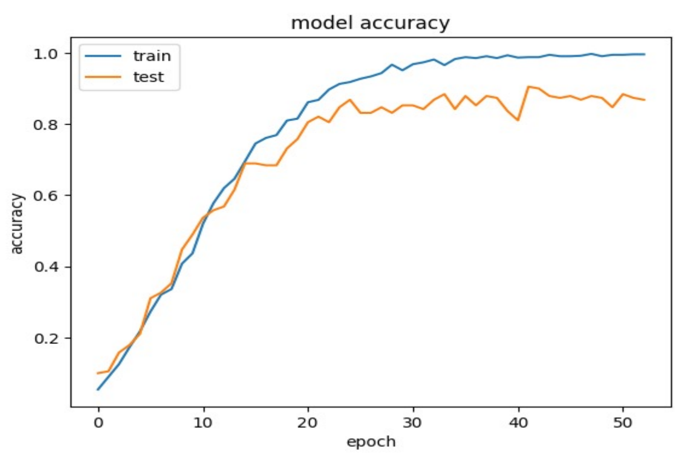

Fig. 5. Accuracy curve for CNN+LSTM training with all 4 channel on AEP dataset

In our second study, we also experimented with the BED: Biometric EEG dataset and assessed the performance of two distinct approaches for biometric identification. First off, analysing all 14 EEG channels at once with a simple CNN and LSTM architecture yielded an accuracy of 89%, as shown by the by the accuracy curve in Fig. 6. Introducing an attention model on top of that couldn't make the model perform any better with a stagnant accuracy of 89% only. These two outcomes offered a performance metric baseline for comparison. We then looked into a more sophisticated approach that made use of ensemble learning strategies. We used ensemble learning to combine predictions from several models trained on separate EEG channels, initially concentrating on just four of them. This method produced a 96% accuracy rate. Using all 14 channels, i.e., modelling them individually and building an ensemble of them through hard voting, yielded 99% accuracy. Similar improvements can be seen in other performance metrics like precision, recall, and F1 score, as shown in Table III.

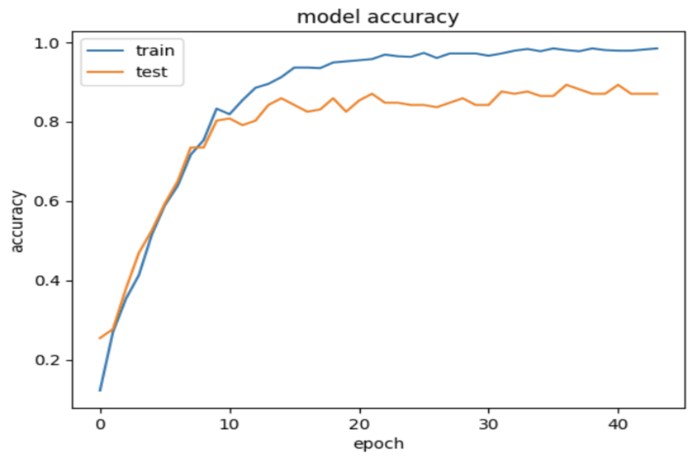

Fig. 6. Accuracy curve for CNN+LSTM training with all 14 channel on BED dataset

The notable improvement in our results, as seen in tables I and IV, highlights the effectiveness of our ensemble learning strategy and shows how it may be used to better utilise the distinct information contained in particular EEG channels for biometric identification. These findings support the possibility of using ensemble learning techniques to improve biometric identification systems' performance.

Comparing our findings with previously published works, our results demonstrate a significant improvement in accuracy, as evident from Tables I and IV. This enhancement underscores the efficacy of our ensemble learning approach in harnessing the unique information embedded in specific EEG channels for improved biometric identification accuracy. These results affirm the potential of ensemble learning methodologies for enhancing the performance of biometric identification systems, particularly when dealing with complex datasets such as the BED.

VI. CONCLUSION AND FUTURE WORK

This research presents a novel methodology for EEG-based biometric identification using the Auditory Evoked Potential EEG-Biometric dataset (AEP dataset) and the Biometric EEG

TABLE III

METRICS COMPARISON BETWEEN MODEL WITH ALL CHANNELS TAKEN AT ONCE VS ENSEMBLE OF CHANNEL INDEPENDENT MODELS (BED DATASET)

Metrics	All channels	Ind.ensemble 14	Ind.ensemble 4
Accuracy	0.89	0.990	0.960
Precision	0.896	0.993	0.970
Recall	0.892	0.996	0.970
F1 score	0.879	0.992	0.965

TABLE IV

ACCURACY COMPARISON BETWEEN PRE-EXISTING MODELS VS OUR PROPOSED MODEL FOR (BED DATASET)

Models	Accuracy
CNN [7]	83.51%
EEGNET [7]	86.74%
CNN + deep FC [8]	98.2%
CNN+LSTM	89.6%
CNN+LSTM with attention	89.3%
CNN+LSTM with Ensemble learning (4 channels)	96%
CNN+LSTM with Ensemble learning (14 channels)	99%

dataset (BED). By leveraging Short-Time Fourier Transform (STFT) for feature extraction, channel-wise processing, and ensemble learning with a hard voting classifier, we achieved high accuracy rates: 98% on the AEP dataset with all 4 individual channels, 96% with all 4 individual channels, and 99% with all 14 individual channels on the BED dataset. These results demonstrate the robustness and reliability of our approach to accurately identifying individuals based on EEG signals.

Future work should focus on evaluating the performance of our methodology over larger populations and multiple session recordings to ensure signal uniqueness and stability over time. Additionally, exploring real-time implementation, scalability, and addressing potential challenges in practical deployment are essential. Further research should also consider advanced model architectures, robustness across diverse demographic groups, and ensuring user privacy and security in EEG data handling. This study lays the groundwork for developing reliable, efficient, and secure EEG-based biometric authentication systems with broad applications in various domains.

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