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EEG-based human recognition using Hjorth-parameters and LSTM technique

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ABSTRACT

There is increasing interest in assessing the feasibility of using Electroencephalography (EEG) signals in biometric purposes. Using deep learning techniques has achieved great performance in classification-based systems in general. However using them in EEG–based human recognition systems still limited, this was the main motivation which encouraged the authors to investigate using of these techniques in EEG-based human recognition system. In this paper, the authors suggested a framework that uses the three Hjorth parameters to enhance the Long-Short Term Memory (LSTM) performance for Electroencephalography (EEG)-based human recognition systems. The proposed framework also investigates the ability to optimize two critical factors of EEG-based biometrics, which are the number of channels and the time needed for acquiring data. The proposed approach has been tested on a public data set, which is the public Texas data repository to verify the improvement of recognition and its reliability through the data recording duration of the eight minutes. The study evaluates two optimizers, namely, Stochastic Gradient Descent optimizer and Conjugate Gradient Descent. The results show a significant improvement in the LSTM performance using the proposed framework, by applying the fusion of features with the Hjorth parameters and using Conjugate Gradient Descent optimizer (CGD).

General Terms

Pattern Recognition, Security, Human Recognition.

Keywords

EEG, Deep learning, Hjorth parameters, LSTM, Conjugate Gradient Descent

1. INTRODUCTION

The advantages of EEG as a biometric over the traditional ones have recently motivated many researchers to use EEG biometric. These advantages [1][2] such as it is produced only by livings (unlike face and finger prints), it is impossible to be copied, highly affected with stress and mood (that makes it hard to enforce subjects to produce the right data), in addition to being suitable for both static and continuous authentication system.

EEG-based identification process can be divided into three main stages, the EEG data acquiring, features extraction, and classification. For EEG data acquiring: different data recording scenarios have been studied in the literature, responding to an audio stimulus [3], responding to a visual stimulus [4], performing tasks [5], relaxing with eyes-closed and relaxing with eyes-opened [6]. And the advantage of the relaxing scenario used in this paper is that it is more applicable and lower cost. For features extraction: Selecting the optimal features for EEG-based biometrics is an essential step. Many features have been used in the literature such as, Autoregressive model features [7][8][9], statistical features [10], and spatiotemporal features [11] while using the Hjorth parameters as features in the EEG-based human recognition is rare. For classification: Many traditional classifications have been used in the previous work such as, K-Nearest Neighbor [12][13], Artificial Neural Networks [14], and Support Vector Machine [15] and the research direction are to the utilizing of the deep learning techniques. EEG-based biometrics is considered one of the most complex human recognition systems [4] and still faces many limitations; two of them studied in this approach are the time of recording data and the number of channels.

Recently, with the significant advances in deep learning techniques, many researchers directed to use them in their studies. Although the significant results that achieved using deep learning techniques in classification problems, they need a large amount of memory and computational resources. This study aims to investigate the ability to use deep learning techniques such as the Long-Short Term Memory LSTM and present a framework that improves its performance using simple computations. The three-Hjorth parameters achieved that objective; they are easy computed and improved the LSTM deep learning technique.

Although using deep learning techniques for EEG-based systems has achieved great results in different purposes such as Pathology detection [4] seizure detection [5], but utilizing them in EEG biometrics purposes is still a great challenge. Many studies have tried to improve the results acquired by using deep learning techniques in EEG-biometrics purposes. Some of these researches are studied in this section.

Member et al. [6] improved the performance of deep learning by making integration between the Conventional Neural Networks (CNN) and the Recurrent Neural Networks. Utilizing stimuli and segmenting the 32-channels of EEG records into 10-seconds length. Supawich Puengdang and Teerapath Sattabongkot [4] used data collected from 20 subjects using seven data channels. They presented an approach that applied a fusion of two kinds of features. Namely, steady-state visually evoked potential and event-related potential features and used the LSTM network for classification purposes. They used the False Acceptance Rate (FAR) and False Rejection Rate (FRR) parameters to evaluate their approach. Where, Mao et al. [16] highlighted the promise of real-life EEG based-biometric recognition deep learning methods. They used data from a driving BCI experiment (using a video stimulus). Participants performed a lane-keeping driving task in a virtual reality platform; the duration of each session was 60 minutes. Their proposed approach depended on the CNN techniques using 64-channel data of one-second epoch's length. Schons et al. [17] used a CNN model on data collected during the subject's relaxation. The epochs were segmented to 12 seconds long and 64 channels. They utilized the data augmentation to overcome the lack of data to train the deep CNN. In their approach, Spampinato et al. [18] used data of 6 subjects recorded using visual stimuli using a 128-channel cap. They used the RNN to learn the discriminative brain activity manifold then transfer the acquired features to the CNN for classification. Arnau-González et al. [19] tested their proposed system on EEG-data recorded using a low-cost device with 16-channel from 23 subjects while watching film clips. The data are segmented to 6-seconds long epochs. The system utilizes the power spectral density features to feed the CNN for classification. El-fiqi et al. [20] used Steady-State Visual Evoked Potentials acquired using visual stimuli of two data sets of four and ten subjects, and they applied the CNN for classification.

Recently, Gupta et al. [21] depended on the eye-blinking to extract features of EEG signals. They used Support Vector Machine for classification. They tested the approach on twenty subjects. The TPR for the one blink one-class case was 60%, while TPR in the cases for 3 and 5 blinks is roughly 73% and rises to about 80% for seven blinks. Comparing these results to the number of participants in their experiments, the results need more improvement to be used in real systems. Chen and Yin [22] presented an access control system based on the 32-channel EEG data for authenticating access control to the car. On the test, the users were asked to look at a computer screen and perform some tasks to simulate the car driving operation. The accuracy of their approach reached 87.3% tested on ten subjects. Comparing to our study, they used 32-channels while our study utilizes only one-channel as 32-channels are very difficult and more expensive in both computations and price. In their study [23], Sabeti et al. used 24-EEG channels system to record data of twenty subjects in two different scenarios resting scenario and the Evoked Related Potential (ERP). Then they extracted the conventional features, and then these features are fed to three different classifiers K-Nearest Neighbor, Support Vector Machine, and Random Forest. In the conclusion of their experiments, they declared that the EEG features extracted during ERP scenario are more distinctive than those extracted during resting. As they declared thee using of ERP scenario gives more data and better results than rest, but rest is less expensive and more easier to be applicable in real systems. Pani et al.[24] enrolled fifteen volunteers in their study to record data using 61 channels EEG system. They executed four different scenarios the eyes-closed with a simple mathematical task, eyes closed with a complex mathematical task, resting with eyes-closed, and resting with eyes-opened. They extracted three different features vectors PSD, PLV, and EC. Their experiments were valuable especially in the scenarios they utilized, but number of 61 channel make the system complex in computations and so need powerful processors and more time.

Comparing to the previous studies, our work presents a comprehensive approach for improving the performance of LSTM and utilizing only data of single-EEG channel recorded in one-second in both eyes-closed and eyes-opened resting scenarios. In addition to, using LSTM which is often better in handling temporal information [6] as a result of the forget gate that can control which information to save and update or discard. And the choice of the dataset to test the proposed approach has 8 minutes of recording to evaluate its stability.

Although the more time of recording EEG data and the more number of channels collecting data from, the better results can be achieved, this approach is hard to be applicable. Also, selecting the resting scenario to test the framework on more applicable systems. The proposed framework has achieved three main contributions:

(i) Depending on EEG data acquired from only one channel.
(ii) Segmenting the data acquired according to time intervals of only one-second epochs.
(iii) Improving the performance of the LSTM technique in classifying EEG data for authentication purposes by using the fusion among EEG data and the three Hjorth parameters is a new technique.

The rest of this study is organized as follows; Section 2 illustrates the proposed framework for person identification using a single EEG channel for the duration of an only one-second epoch. Section 3 shows the details of the conducted experiments and declares the obtained results in two scenarios, which are the resting closed-eyes and resting opened-eyes. Section 4 introduces the conclusion and future work.

2. PROPOSED FRAMEWORK

In this section, the authors illustrate the proposed framework for EEG-based human recognition in the three stages, preprocessing, features extracting, and classification. Figure (1) shows the proposed framework.

2.1 Preprocessing

In this approach, we depended on using all the power of EEG signal, which are Delta, Theta, Alpha, Beta, and Gamma. The reason is to acquire all the information linked to the psychological states and the cognitive brain functions of subjects. Then, extract the data of only one channel (Iz) and which are sampled at 256 Hz then segment it to only one-second-long epochs.

2.2 Feature extraction

Hjorth parameters have been confirmed as efficient features in many EEG-based systems for different purposes [25][26][27][28]. While using them for EEG-biometric purposes are rare. In this approach, we utilized a fusion between them and all the samples acquired from the 256 sampling rate of the signal.

The three parameters of the Hjorth are computed according to the next equations [29][30]:

$$Activity = \sigma_x^2 \qquad (1)$$

$$Mobility = \sqrt{\frac{\sigma_d^2}{\sigma_x^2}} = \frac{\sigma_d}{\sigma_x} \qquad (2)$$

$$Complexity = \sqrt{\frac{\frac{\sigma_{dd}^2}{\sigma_d^2}}{\frac{\sigma_d^2}{\sigma_x^2}}} = \frac{\frac{\sigma_{dd}}{\sigma_d}}{\frac{\sigma_d}{\sigma_x}} \qquad (3)$$

Where Activity represents the means of the amplitude variance, Mobility is the relative average slope, and Complexity is the ratio between the mobility of the first derivative and the mobility.

Then, these features are optimized using Conjugate Gradient Descent (CGD) [31]. These methods have attracted attention in solving optimization problems [32] because of its simplicity and need limited memory. These properties encouraged researchers to utilize them in large dimensions and unconstrained problems widely. The obtained features are then fed to the LSTM network for classification.

2.3 Classification

As Recurrent Neural Networks (RNN) are trained depending on Back Propagation through Time technique, it is difficult to them to learn long sequences that is known as vanishing gradient problem. A widely used type of RNN is LSTM technique, which replaces the RNN cell by a gated cell to control which information has to be remembered and which are not in the long sequences [33], hence it is more appropriate for EEG data. LSTM consists of memory cells and memory blocks; memory block consists of input, forget, and output gate [34]. The input gate controls the flow of the inputs to the cell and selects which new information is to be saved and updated. The output gate controls which output of the cell is used and which will be sent to another LSTM blocks. The forget gate consists of a one-layered neural network that evaluates information and discard the redundant from the cell and decides the extent to which the information remains in the cell. The activation of forget gate is denoted by F_t which is calculated according to (4).

$$F_t = \sigma\,(\,W\,[\,X_t, H_{t-1}, C_{t-1}] + b_f) \qquad (4)$$

Where σ represents the sigmoid function to a weights sum, W is the weight vector for each input, X_t denotes the sequence of input, H_{t-1} denotes the output of the previous block, C_{t-1} is the block memory of the previous LSTM, and b_f represents the bias vector of the forget gate.

If the value of the activation output vector is near zero, then the foregoing memory will be forgotten. The activation of the input gate is labeled by I_t, which can be calculated according to (5).

$$I_t = \sigma(\,W[\,X_t, H_{t-1}, C_{t-1}] + b_i) \qquad (5)$$

The output of the LSTM is calculated according to (6) and (7).

$$O_t = \sigma\,(\,W[X_t, H_{t-1}, C_{t-1}] + b_0) \qquad (6)$$

$$H_t = \tanh(C_t)\,.\,O_t \qquad (7)$$

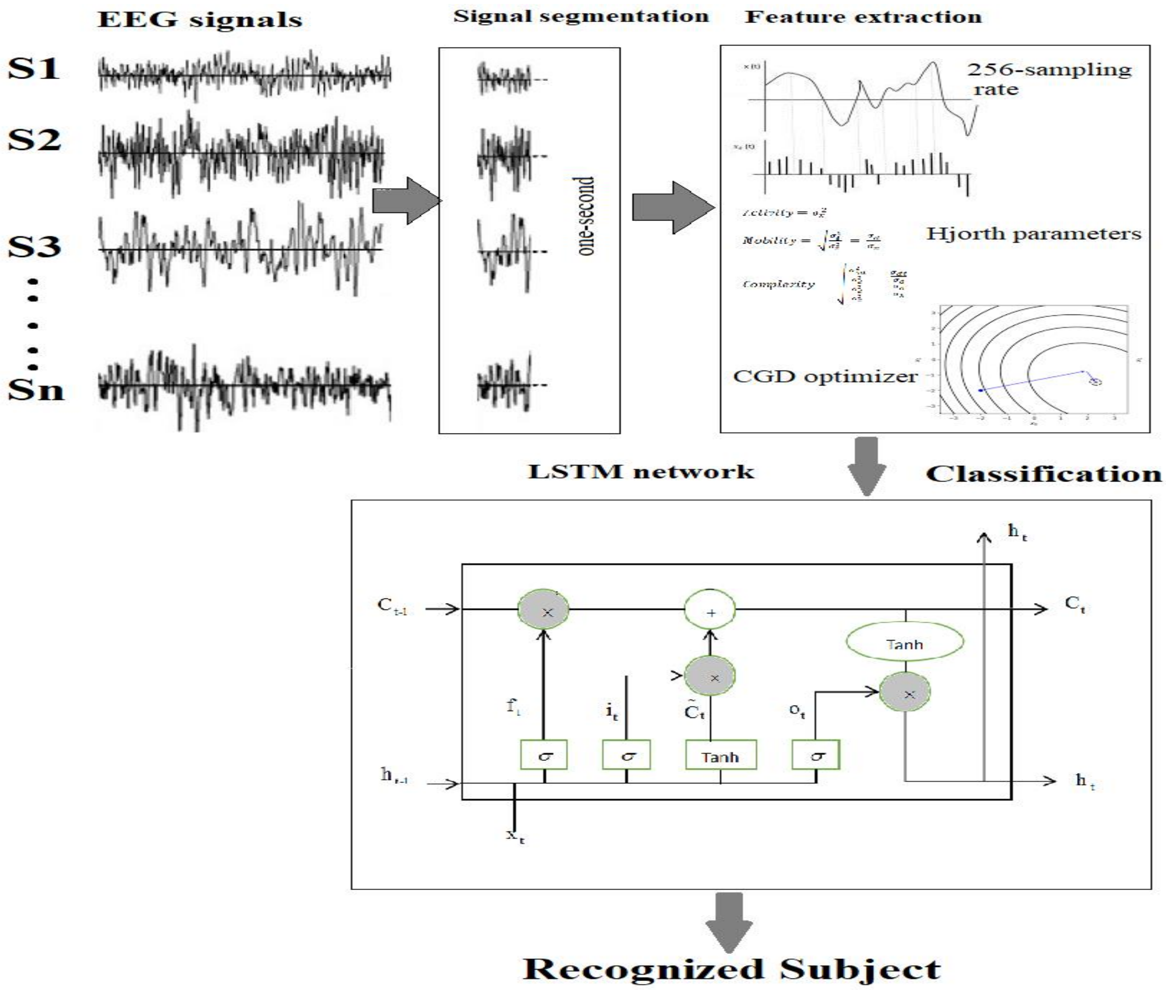


Fig 1: The proposed framework

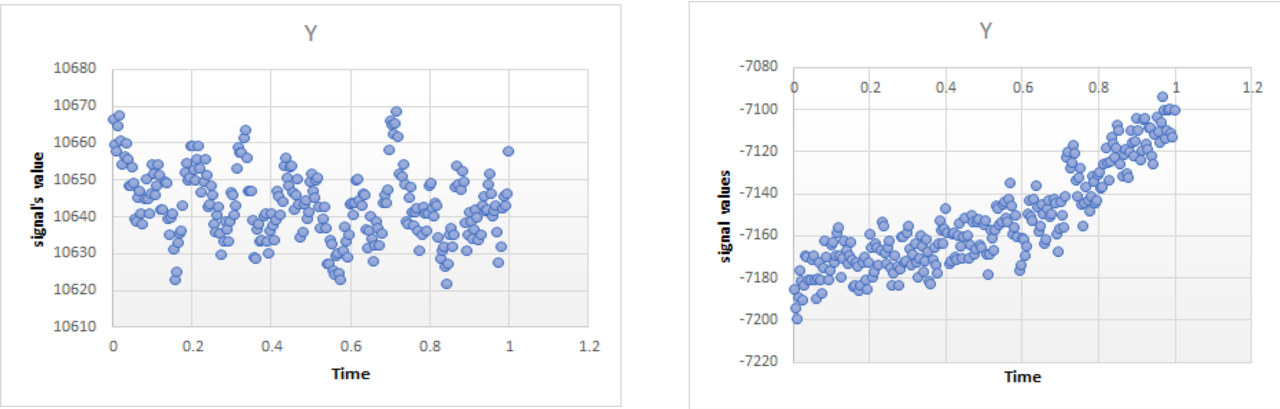
3. EXPERIMENTAL RESULTS

In this study, all the experiments were run on a GPU-accelerated machine with Nvidia GeForce MX150 and ACPI x64-based pc, Using the Waikato Environment for Knowledge Analysis 3.8.3 tool (WEKA 3.8.3) [35]. The EEG signals were preprocessed using the Matlab EEGlab-toolbox [36].

For examining the accuracy and the stability of the proposed approach, authors selected the public Texas data repository [37] to do the experiments on it. The data in this repository are acquired from 22 subjects, four minutes recording of subjects' eyes-closed and, four minutes while subjects' eyes-opened. In such that minutes 1, 3, 5, and 7 are recorded with subjects' eyes-closed and minutes 2, 4, 6, and 8 are recorded with subjects' eyes-opened. Concerning subject 6, only recorded two minutes with eyes-closed that enforced the authors to exclude him/her from the experiments. Dataset has been segmented to two partitions 11 subjects as genuine and 10 subjects as imposters, examining each subject of the imposters in a separate experiment. The experiment is repeated 10 times each time an imposter is checked to check the accuracy of the approach to recognize that imposter. Data of the Iz channel is extracted. Then partition signals into 1-sec epochs long, and exclude the first and last epoch of each minute; the result is 1218 instances for each minute and 4872 instances for the 21 subjects for each scenario. After that, authors have extracted Hjorth parameters of each epoch and applied the features fusion technique to acquire the features that will be fed to the LSTM. To validate the performance of the proposed approach, we conducted two experiments: In experiment 1, the eyes-closed scenario has been verified. And in experiment 2, the eyes-opened scenario has been verified.

3.1 Experiment 1

In this experiment, we applied the proposed framework to the eyes closed scenario. Examples of the acquired epochs for subjects 20 and 21 are shown in figures 2a and 2b.



(a) (b)

Fig 2: (a) Subject 20 signals during eyes-closed scenario (b) Subject 21 signals during eyes-closed scenario

To investigate the influence of using the Hjorth parameters on the LSTM, we Use the True Positive Rate (TPR) evaluator calculated according to equation (8).

$$TPR = TP/(TP + FN) \quad (8)$$

Where TP is True Positive and FN is False Negative.

the results achieved using the proposed framework are compared to (i) using the LSTM technique on EEG data without the Hjorth parameters and using CGD (ii) using Hjorth parameters and applying SGD optimizer and (iii) Applying SGD without Hjorth parameters. Table 1 presents the results achieved. Figures 3, 4, 5, and 6 show a comparison of the results achieved for the four minutes of eyes-closed scenario. As illustrated, a significant improvement in the performance of LSTM has been achieved using the proposed framework.

The results proof that the Hjorth parameters improve the performance of LSTM this is because they support the classifier with unique features that enhance its performance.

Table 1: results of the eyes closed scenario represented in minutes 2, 4, 6, and 8

Min2	stoch.	Conj.	stoch.+HjP	**Conj.+HjP**
sub13	68.77	75.1	91.56	**91.98**
sub14	75.1	75.1	75.9	**89**
sub15	66.7	66.7	91.1	**94.9**
sub16	70.88	74.68	88.6	**91.56**
sub17	70.46	70.46	84.8	**85.2**
sub18	64.98	64.98	91.1	**91.98**
sub19	64.98	75.1	91.56	**91.98**
sub20	60.5	60.5	71.35	**73.1**
sub21	60.5	60.5	71.77	**75.99**
sub22	60.5	60.5	70.1	**73.88**

Min4	stoch.	Conj.	stoch.+HjP	**Conj.+HjP**
sub13	72.8	78.8	93.55	**94.01**
sub14	66.24	75.9	89.87	**90.3**
sub15	62.87	72.15	89	**89.45**
sub16	72.57	75.95	88.6	**89.87**
sub17	66.24	74.26	88.61	**91.14**
sub18	65.82	74.26	91	**91.56**
sub19	70.04	72.99	84.39	**89.03**
sub20	54.18	60.5	72.62	**74.73**
sub21	39.83	52.07	71.35	**75.99**
sub22	52.49	60.5	72.6	**75.15**

Min6	stoch.	Conj.	stoch.+HjP	**Conj.+HjP**
sub13	65.82	75.95	86.08	**86.92**
sub14	59.07	68.35	87.76	**88.19**
sub15	61.6	67.51	87.34	**87.76**
sub16	59.07	69.2	81.86	**83.12**
sub17	75.95	75.95	88.6	**89.45**
sub18	65.82	69.2	78.48	**82.28**
sub19	75.95	75.95	84.39	**87.76**
sub20	52.06	52.07	69.67	**70.08**
sub21	52.07	52.07	65.87	**69.67**
sub22	52.07	52.07	65.87	**66**

Min8	stoch.	Conj.	stoch.+HjP	**Conj.+HjP**
sub13	65.82	71.3	85.65	**86.5**
sub14	59.07	65.4	81.86	**82.7**
sub15	62.02	65.82	81.43	**84.8**
sub16	59.07	66.67	78.9	**83.12**
sub17	82.7	84.39	85.23	**85.66**
sub18	65.8	69.6	77.2	**78.1**
sub19	69.2	82.7	82.7	**85.2**
sub20	57.55	60.5	72.2	**72.6**
sub21	52.07	57.13	69.24	**70.92**
sub22	52.07	57.55	69.24	**71.35**

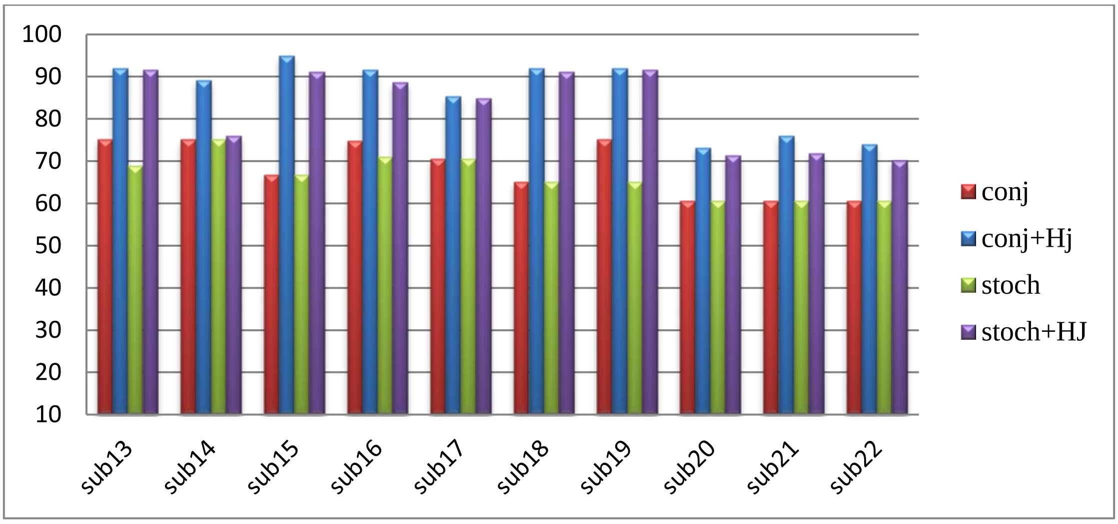


Figure 3 min 2

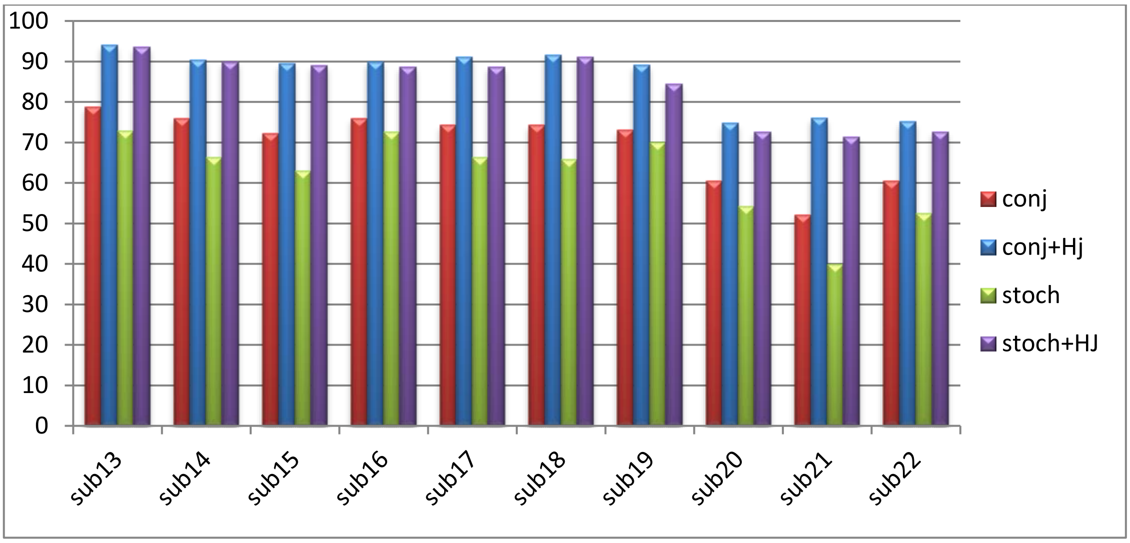


Figure 4 min 4

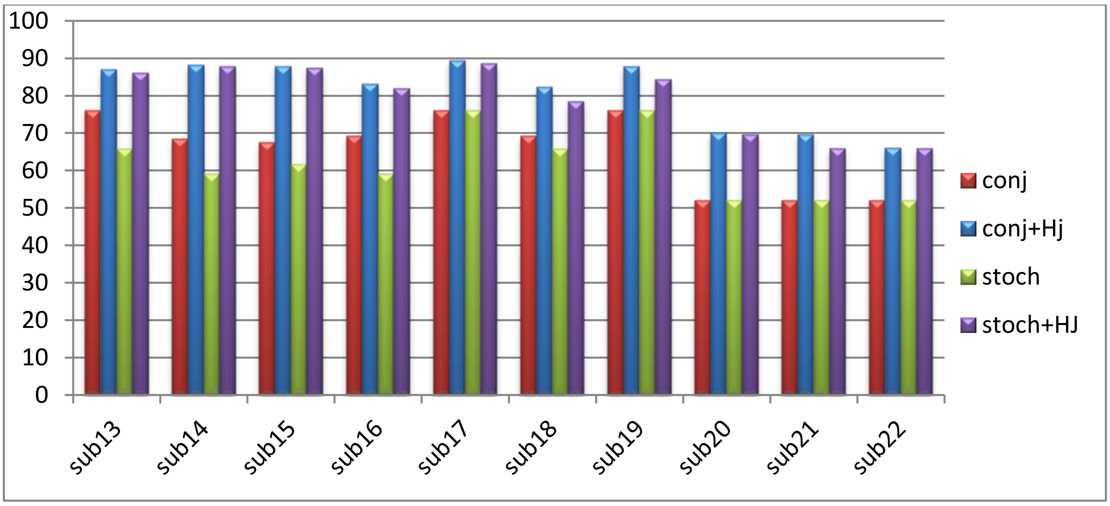


Figure 5 min 6

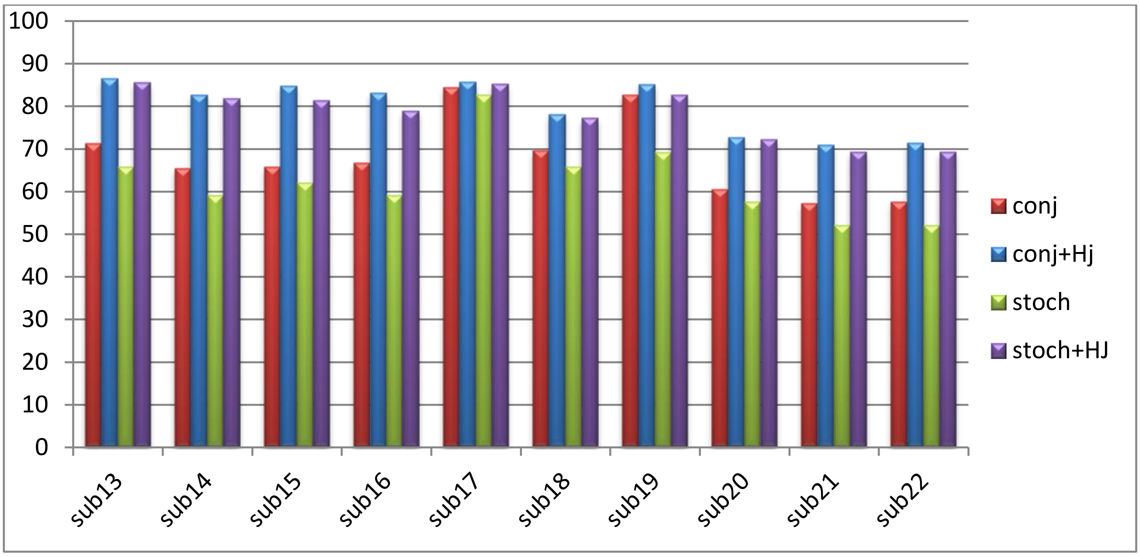
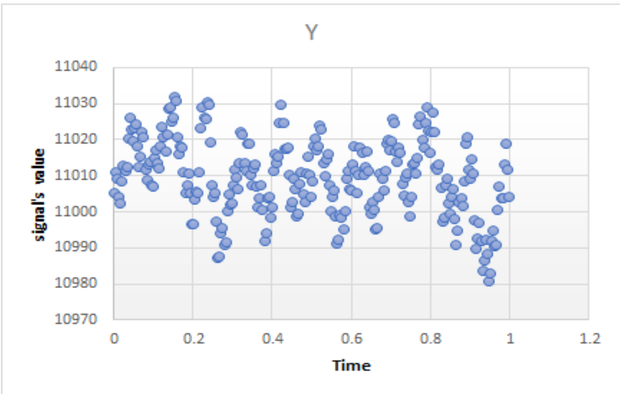


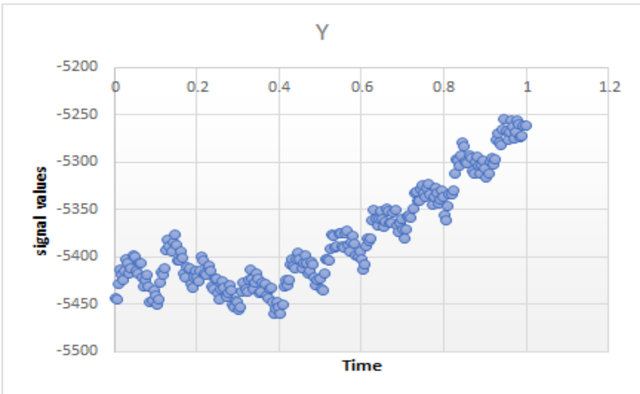
Figure 6 min 8

3.2 Experiment 2

In this experiment, we applied the proposed framework to the Eyes-opened scenario. Examples of the acquired epochs for subjects 20 and 21 are shown in figures 7a and 7b.



(a)



(b)

Fig 7: (a) Subject 20 signals during eyes-opened scenario (b) Subject 21 signals during eyes-opened scenario

To investigate the influence of using the Hjorth parameters on the LSTM, we used the True Positive Rate (TPR) evaluator calculated according to equation (8). The results achieved using the proposed framework are compared to (i) using the LSTM technique on EEG data without the Hjorth parameters and using CGD optimizer (ii) using Hjorth parameters and applying SGD optimizer and (iii) Applying SGD without Hjorth parameters. Table 2 presents the results achieved. Figures 8, 9, 10, and 11 show a comparison of the results achieved for the four minutes of eyes-opened scenario.

The results show that the Hjorth parameters have not been affected by the eye blinking while LSTM is greatly affected; this explains the decrease in results when using LSTM without the Hjorth parameters in the open eyes scenario than the closed eyes scenario. And this proves that using Hjorth parameters on the raw EEG data is effective.

Table 2: Results of the eyes opened scenarios represented in minutes 1, 3, 5, and 7

Min1	stoch.	Conj.	stoch.+HjP	**Conj.+HjP**
sub13	6.78	6.78	84.32	**88.14**
sub14	14.4	14.4	84.3	**87.3**
sub15	14.4	14.4	74.6	**78.8**
sub16	14.4	14.4	84.3	**88.14**
sub17	13.1	14.4	79.66	**80.5**
sub18	7.6	7.6	86.4	**86.9**
sub19	14.4	14.4	85.6	**85.6**
sub20	14.4	14.4	69.8	**70.7**
sub21	14.4	14.4	69	**70.7**
sub22	14.4	14.4	69.4	**70.25**

Min3	stoch.	Conj.	stoch.+Hj P	**Conj.+Hj P**
sub13	8.05	8.05	88.98	**90.68**
sub14	10.2	10.2	78.8	**79.2**
sub15	10.2	10.2	82.4	**83.9**
sub16	10.2	10.2	79.7	**88.98**
sub17	10.2	10.2	88.14	**89.4**
sub18	10.2	10.2	87.4	**88.1**
sub19	20.3	20.3	83.5	**87.3**
sub20	10.2	10.2	74.5	**74.9**
sub21	13.5	13.5	74.9	**74.9**
sub22	10.2	10.2	82.1	**83.8**

Min5	stoch.	Conj.	stoch.+Hj P	**Conj.+Hj P**
sub13	24.9	24.9	84.1	**85.6**
sub14	24.9	24.9	77.6	**82.3**
sub15	22.4	24.9	76.1	**77.2**
sub16	24.9	24.9	75.5	**83.5**
sub17	24.9	24.9	84.9	**85.2**
sub18	24.9	24.9	84.8	**85.7**
sub19	24.9	24.9	83.9	**84.4**
sub20	24.9	24.9	63.7	**64.6**
sub21	24.9	24.9	65	**65.9**
sub22	24.9	24.9	64.2	**65.4**

Min7	stoch.	Conj.	stoch.+Hj P	**Conj.+Hj P**
sub13	22.9	22.9	78.4	**87.3**
sub14	13.1	13.9	74.6	**81.8**
sub15	16.9	16.1	79.5	**80.1**
sub16	13.1	17.4	76.7	**78.4**
sub17	17.4	16.1	81.8	**87.3**
sub18	22.5	16.1	78.4	**78.4**
sub19	17.4	16.9	79.7	**80.5**
sub20	19.9	16.1	71.9	**76.6**
sub21	13.1	22.5	72.3	**73.6**
sub22	17.4	17.4	72.6	**75.3**

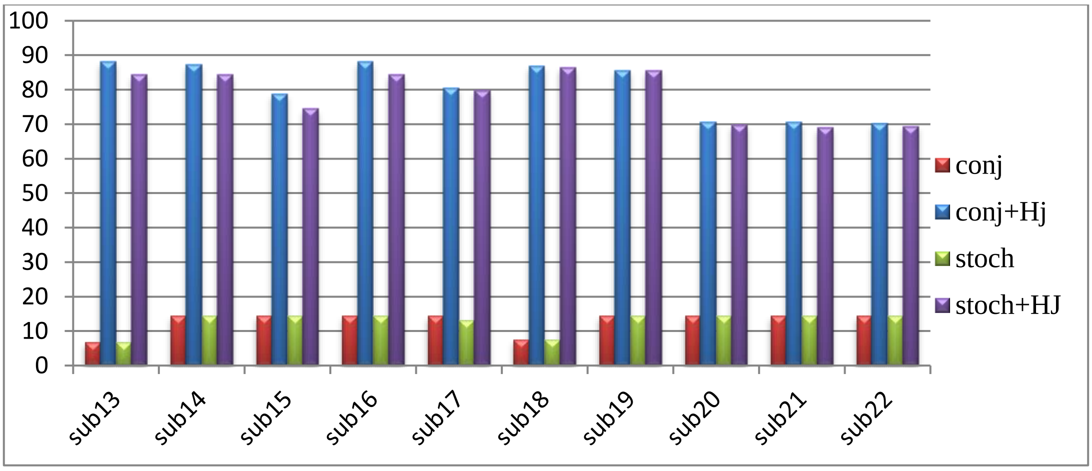


Figure 8 min 1

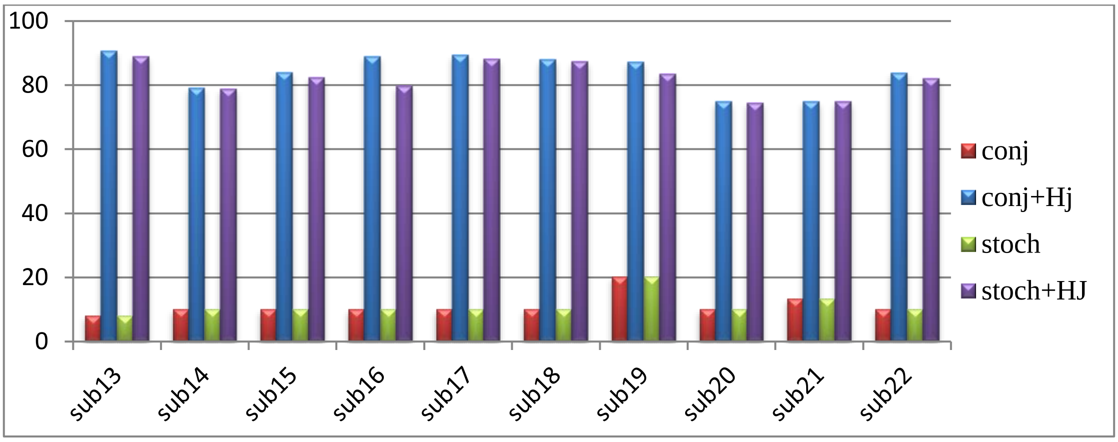


Figure 9 min 3

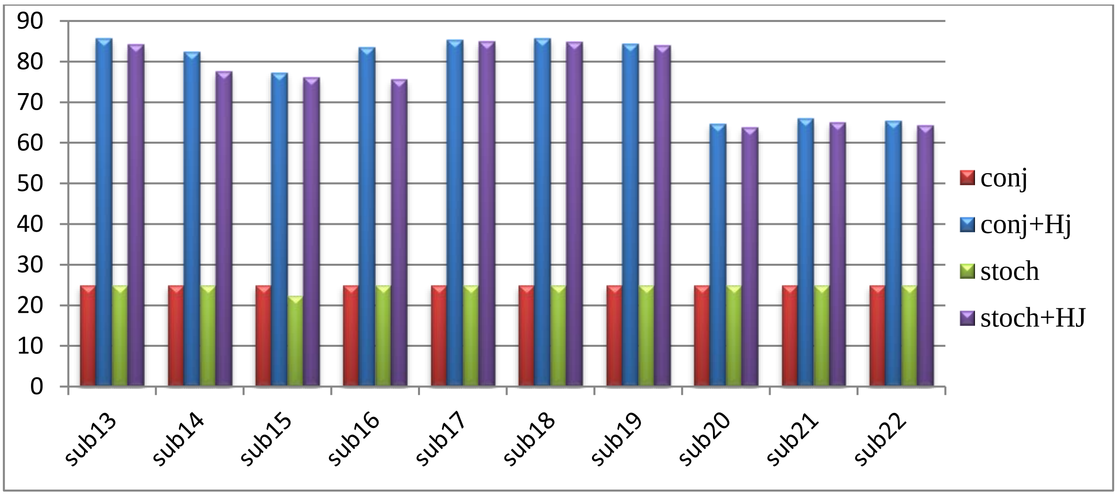


Figure 10 min 5

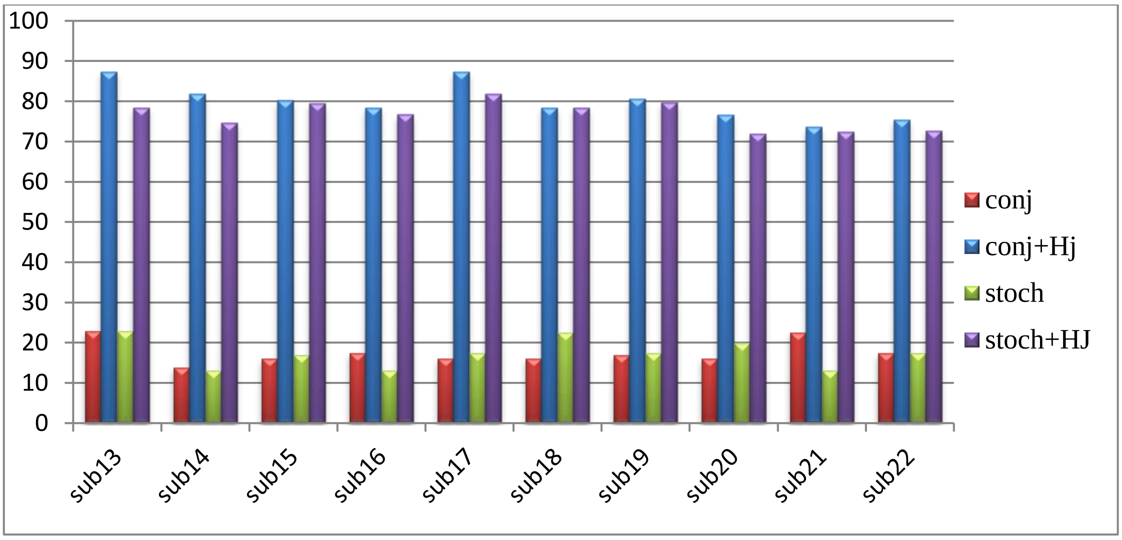


Figure 11 min 7

4. CONCLUSION AND FUTURE WORK

Although the EEG many-channel based biometrics could achieve better results than single-channel ones because of acquiring much data, the less the number of channels, the more applicable, less cost, and more friendly the system is. The same is the time factor; the longer the session of acquiring data, the better results could be acquired, but the less comfortable for the users. The achieved results demonstrate the ability to reduce the number of channels of EEG to only one channel and the duration to only one second. Using the Hjorth-parameters can support the EEG-based recognition systems with unique features that can improve the performance; uniquely if they are integrated with the CGD optimizer and deploying the LSTM network for classification purposes. The advantage of using these parameters is that they are easy to be calculated and not need much time or high processing capabilities. Another critical point is observed from the results of the eyes-opened scenario, which produces very low accuracy without using the Hjorth parameters. Using these parameters greatly improves the efficiency of the raw data (without using any filters to discard the eye blinking data).

In the future, the proposed approach will be tested on bigger data sets, and more studies on the best EEG-channel results will be conducted. As well, doing more research on the LSTM technique and checking the efficiency of other optimizers to improve the results. Although continuous authentication is relatively new, it is receiving significant attention due to the rapid speed of digital development and the escalation of cybercrime. EEG-based human recognition is considered an ideal solution for continuous authentication, unlike other biometrics such as the face, finger iris, and even passwords. So, A lot of research needs to be carried out, on deploying EEG for continuous authentication purposes; particularly, after the significant development of wearable and smart devices.

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