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# fNIRS: A New Modality for Brain Activity-Based Biometric Authentication

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## Abstract

*There is a rapidly increasing amount of research on the use of brain activity patterns as a basis for biometric user verification. The vast majority of this research is based on Electroencephalogram (EEG), a technology which measures the electrical activity along the scalp. In this paper, we evaluate Functional Near-Infrared Spectroscopy (fNIRS) as an alternative approach to brain activity-based user authentication. fNIRS is centered around the measurement of light absorbed by blood and, compared to EEG, has a higher signal-to-noise ratio, is more suited for use during normal working conditions, and has a much higher spatial resolution which enables targeted measurements of specific brain regions. Based on a dataset of 50 users that was analysed using an SVM and a Naïve Bayes classifier, we show fNIRS to respectively give EERs of 0.036 and 0.046 when using our best channel configuration. Further, we present some results on the areas of the brain which demonstrated highest discriminative power. Our findings indicate that fNIRS has significant promise as a biometric authentication modality.*

## 1. Introduction

Given the well known drawbacks of password-based authentication, there is now a significant amount of interest in the Active Authentication paradigm (e.g., see recent research efforts such as DARPA's Active Authentication program [1], and AFRL's Mobile Android Multi-Biometric Acquisition program [2]). The major security benefit offered by Active Authentication (AA) stems from the fact that a user is monitored throughout a session of interaction with the computing device, making it exceedingly difficult for a masquerader to pose as the genuine user. This is in stark contrast to a password-based authentication setting where a user is verified *once* before being granted access, leaving the system vulnerable to any adversary holding the password.

While AA is perhaps best understood from the perspective of behavioral patterns (e.g., keystroke, mouse and touch dynamics), recent work has revealed that neural patterns, such as those manifested by a user's brain activity during different mental tasks, also hold significant promise as an AA modality. Monitoring these patterns using Electroencephalogram (EEG) sensors, several studies have showcased classification accuracies in the 80% to 90% range (e.g., see [16][14]) depending on the tasks being performed by the users during authentication.

In this paper, we extend the state-of-the-art in brain activity-based user authentication and introduce Functional Near-Infrared Spectroscopy (fNIRS) as an AA modality. The basic mechanism behind fNIRS is that neural activity in the brain during different mental tasks causes changes in blood flow, which can be measured by monitoring the changes in (near-infrared) light absorbed by the blood (see details in Section 3). Relative to EEG, fNIRS has a plethora of advantages, some of which include a higher level of practicality for use in normal working conditions, a much higher signal-to-noise ratio, and significantly higher spatial resolution (see details in Section 3). Although fNIRS is fast becoming mainstream in domains such as Human Computer Interaction (see some recent works [11][23]), it is surprisingly yet to receive significant attention from the biometrics authentication community.

The only work to have examined fNIRS as a user verification modality is the 2-page abstract by Heger et al. [9]. Different from our work however, the abstract reported results based on a very small user population (of just 5 users), used a very small fNIRS device (with less than a sixth of the number of channels used in this work), did not provide any insights into the traits depicted by the different features or brain regions, and focused on the *user identification* problem. To the best of our knowledge, ours is the first paper to examine fNIRS as a *user authentication* modality, let alone to explore the credentials of fNIRS as a biometric modality in details on a large dataset. The contributions of this paper are summarized below:

1. Based on a 50-user dataset collected using a 52-channel fNIRS device, we evaluate fNIRS as an authentication modality. Respectively using an SVM and

Naïve Bayes classifier, we show fNIRS to give Equal Error Rates of 0.043 and 0.063 when data from all 52 channels is used for authentication and Equal Error Rates of 0.036 and 0.046 when a sub-set of channels having highest discriminative power is used. Our work represents the first steps towards the use of fNIRS as an AA user authentication modality.

2. We analyze the variations of feature discriminative power across brain regions and present findings on which regions of the brain discriminated between users best while they completed the simple addition tasks that were used during our experiments. The most predictive brain regions for authentication were regions that have been found to be highly sensitive to addition tasks in prior neuroscience literature.

The rest of the paper is organized as follows. In Section 2, we discuss related work and provide insights into non-invasive brain measurement in Section 3. We describe our data collection experiments in Section 4 and present the fNIRS performance evaluation results in Section 5. We finally make our conclusions in Section 6.

## 2. Related Work

A great deal of prior research has explored biometric authentication using a range of physiological and behavioral user metrics. Approaches to biometric authentication and identification vary with respect to the features and techniques used. In terms of features, users periocular regions [4], eye gaze patterns [20], cardiac biometric patterns [8], fingerprints [5], and facial features [12] or combinations thereof, have all been used to support the development of automated authentication and identification systems.

Prior research has also explored brain activity measurement as a way to authenticate users. Ideally, a brain measurement device suitable for biometric authentication and identification under normal working conditions would be non-invasive and portable. It would have fast temporal resolution and high spatial resolution, enabling the localization of brain activation in specific functional brain regions. The EEG has been the most studied device used to measure brain activity during naturalistic human-computer interactions (e.g., see [16][14]), while the relatively new fNIRS device has been gaining momentum in several research domains in recent years. The EEG measures the waves generated by cascading electrochemical signals produced by the firing of neurons while the fNIRS captures blood flow to brain regions to support the firing of neurons.

EEGs have been available for over one hundred years in the research domain, while fNIRS was only introduced in the past twenty-five years; therefore EEGs are much more likely to be used in biometric verification research. Prior research using EEGs for biometric verification involves brain measurement while the subjects are at rest [16][3] or engaged in a task that stimulates brain regions associated with verbal [16] spatial [18], or arithmetic work [18]. However, when compared to fNIRS, EEG devices are more susceptible to noise, both from ambient sources (e.g., electrical systems in buildings), and motion artifacts. Also, EEGs have lower spatial resolution than fNIRS, making it difficult to determine the actual regions of the brain that are stimulated at any given time. EEG's limitations make fNIRS an attractive alternative for biometric verification using brain measurements.

As mentioned previously, there has only been one prior publication studying the potential of fNIRS for user verification. This 2-page abstract by Heger et al. [9] used a very small user population (n=5) for *user identification*, making it difficult to determine the scalability of the results and providing no insights at all into the *user authentication* problem that is the focus of this paper. Additionally, the fNIRS device used by Heger et al. was only capable of measuring 8 points in users brains (our configuration, described below, collects 52 measurement locations), and they do not include any detail about the actual regions of the brains that were predictive of user authentication on their dataset.

## 3. Non-Invasive Brain Measurement

There are several brain measurement devices available in medical and research domains. These devices monitor brain activation by measuring several biological metrics. When a stimulus is presented, neurons fire in the activated region(s) of the brain, causing an electric potential, an increase in cerebral blood flow in that region, an increase in the metabolic rate of oxygen, and an increase in the volume of blood flow. All of these factors contribute to the blood oxygen level dependent (BOLD) signal, which can be detected (in various forms) by a number of brain measurement techniques such as fMRI, fNIRS, and PET[6]. Ideally, a brain measurement device suitable for measuring brain activity in typical HCI activities would be non-invasive and portable. It would have extremely fast temporal resolution (for use in adaptive systems) and it would have high spatial resolution, enabling the localization of brain activation in specific functional brain regions. Electroencephalograph (EEG) and fNIRS are the two most popular devices for non-invasive imaging of the brain. However, when compared to EEG, fNIRS has higher spatial resolution, lower set-up time, and a higher signal-to-noise ratio [19]. We focus on fNIRS, as this is one of the best suited technologies for non-invasive brain measurement during naturalistic human-computer interactions.

### 3.1. Functional Near-Infrared Spectroscopy

As described above, fNIRS is a relatively new non-invasive technique introduced in the late 1980s [7] to over-

come many of the drawbacks of other brain monitoring techniques. The tool, still primarily a research modality, uses light sources in the near infrared wavelength range (650-850 nm) and optical detectors to probe brain activity.

Light source and detection points are defined by means of optical fibers held on the scalp with an optical probe. Deoxygenated (Hb) and oxygenated hemoglobin (HbO) are the main absorbers of near infrared light in tissues during hemodynamic and metabolic changes associated with neural activity in the brain. These changes can be detected by measuring the diffusively reflected light that has probed the brain cortex. fNIRS has been used in recent years to measure a myriad of mental states such as workload, deception, trust, suspicion, frustration, types of multi-tasking, and stress [22][10].

## 4. Experiment

The goal of our experiment was to authenticate a participant based solely on his or her previously acquired brain data. Three mental tasks were chosen for the experiment, as we were interested in learning which tasks yielded brain data that was more predictive of participant identification. These tasks, and the experiment protocol, are described next.

### 4.1. Experiment Tasks

In the experiment, three conditions, or tasks, were chosen based upon a review of psychological and neuroscience literature to produce consistent patterns of brain activation for the later identification of subjects. All experiment tasks were created using Microsoft Powerpoint. The first condition that subjects were given was called Phone-number recall. During this task, participants were instructed to think of their phone number repeatedly for a twenty second period of time. The next condition was called Addition. This task began with a slide instructing participants to start with x, where x was a small number under 10, such as 5. Next, new slides appeared with instructions such as add 6 or add 9 (with no values greater than 9 to be added at a time). Each addition slide was displayed for 2 seconds, and participants were told to keep a running sum as new numbers appeared. The last slide of the addition section instructed the participant to tell the experimenter the total sum of all of the numbers. The third mental task was called Controlled Rest. Participants were told to relax and clear their minds during this task. The controlled rest task was included in order to determine if it was possible to identify participants during their resting state.

### 4.2. Experiment Protocol

Fifty subjects (37 male) participated in the experiment. Subjects were students from a school in the Northeast. Informed consent was obtained, and participants were compensated for their time. We used a randomized block design, with the three experimental conditions described previously. Each task lasted 20 seconds and a ten-second rest period was placed after each task, allowing participants brains to return to baseline. In each measurement session, there were four experimental blocks (3 conditions x 4 blocks = 12 tasks per session).

Each subject completed a total of four measurement sessions (see Figure 1). The first and second sessions were completed in the morning and afternoon, respectively, of data collection day one. The third and fourth sessions were completed in the morning and afternoon, respectively on data collection day two, which was completed two weeks after data collection day one.

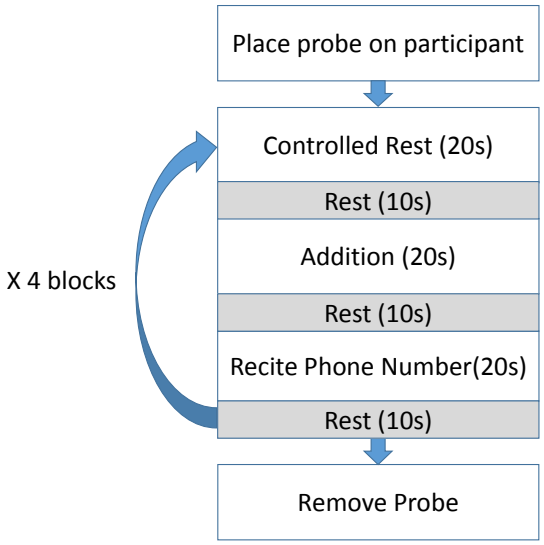



Figure 1: Model of the chronology of tasks users undertook during each measurement session.

All sessions were identical in their experiment layout and the fNIRS cap was newly placed on the subject at the beginning of each session, with the probe centered on each participant's forehead. Before beginning the first session of the experiment, subjects were informed about the tasks and given an opportunity to practice the tasks. They were told that the tasks would appear in a random order. They were then given the opportunity to ask any questions they had about the experiment. Once it was clear that the participants understood the tasks, the fNIRS cap was placed on the participant and the PowerPoint presentation was started. The fNIRS device used in this experiment was Hitachi Medical's ETG4000, with a sampling rate of 2Hz. Participants wore a 52-channel cap (see Figure 2), comprised of 17 light sources and 16 detectors.

Figure 2: A subject wearing the 52-channel fNIRS device in our lab

# 5. Performance Evaluation

## 5.1. Feature Extraction and Analysis

For each of the 52 channels, the raw light intensity dataset was preprocessed to generate changes in oxyhemoglobin, deoxyhemoglobin, and total hemoglobin. All subsequent analysis in this paper is based on the changes in oxyhemoglobin ($\Delta HbO$) which were obtained while users undertook the addition task (see Section 4.1 for details of the tasks). We first carried out a min-max normalization to scale all channels to the range $0 - 1$ before feature extraction. From each channel we then extracted eight features from the 41 data points registered during each 20-second instance of the mathematical task. These features were: (1) standard deviation of first 10 points, (2) standard deviation of the last 10 points, (3) standard deviation of the points in the middle segment, (4) mean of the first 10 points, (5) mean of the last 10 points, (6) mean of the points in the middle segment, (7) maximum value and (8) minimum value.

To determine which features had the highest discriminative power, we used the relative mutual information, $I_R$ between each feature and the class labels (also used in [17]). Let $F$ denote a vector containing the outputs of a given feature across the population and $C$ denote a vector of class labels. $I_R$ is computed as the ratio of $I(F;C)$ to $H(C)$ where $I(F;C)$ is the mutual information between $F$ and $C$ and $H(C)$ is the entropy of $C$. $I_R$ varies between 0 and 1, with values tending towards 1 indicating highest discriminative power. $F$ being a continuous variable, we discretized it (using 20 equally spaced bins) before computing $I(F;C)$.

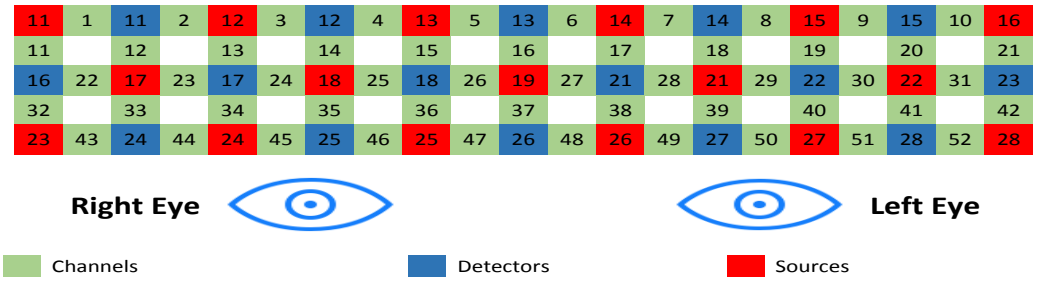
Figure 3 shows how the discriminative power of two features (i.e., the mean of the first ten points and the standard deviation of the last ten points) varied across the 52 channels. Figure 3(a) shows the locations of each of the 52 channels relative to each other and relative to the position of the eyes, while Figures 3(b) and 3(c) respectively show how $I_R$ varied across the channel space for the two above mentioned features. A dark red color indicates a region that had very high discriminative power while a dark blue color indicates a region of very low discriminative power. Note that the $I_R$ values are represented as percentages (see color to $I_R$ mapping at the extreme right of the plots). From the figure, it is apparent that the mean of the first ten points separated users better than the standard deviation of the last ten points (which was one of our worst performing features). Regardless of the performance gap between the two features, the figures reveal an interesting trait: regions around the lower part of the face were more discriminative than those at the upper parts. In Section 5.2 we leverage this information to fine-tune our classification methodology. Note that the feature analysis described above was only applied to a training subset of the dataset. The question of whether these feature analysis findings generalize to the testing dataset is one of those questions to be addressed in the next section.

## 5.2. Authentication Results

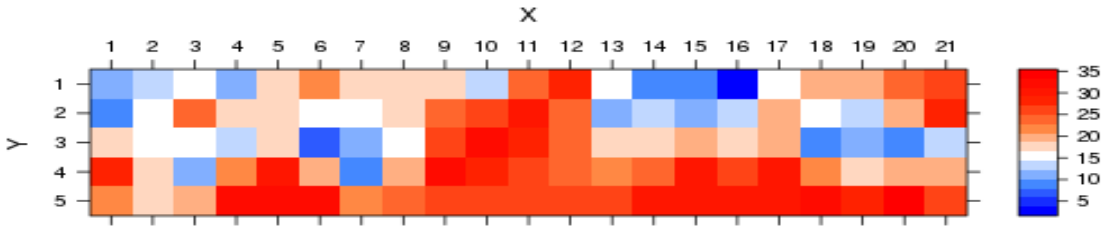
### 5.2.1 Mean and User-level Error Rates

To cut down on the high dimensional feature space and also speed up the learning process, we dropped the two worst performing features (on basis of mean $I_R$) and retained 5 features per channel. Classifier training (i.e., template building) was done based on data collected on the first day while testing was done based on data collected on the second day (recall experiment sessions in Section 4.2). To conduct impostor tests against a given user, we used 15 samples randomly drawn from the other (49) users. To test a user's template against the user's own samples (i.e., genuine testing), we used all data provided by the user on the second day.

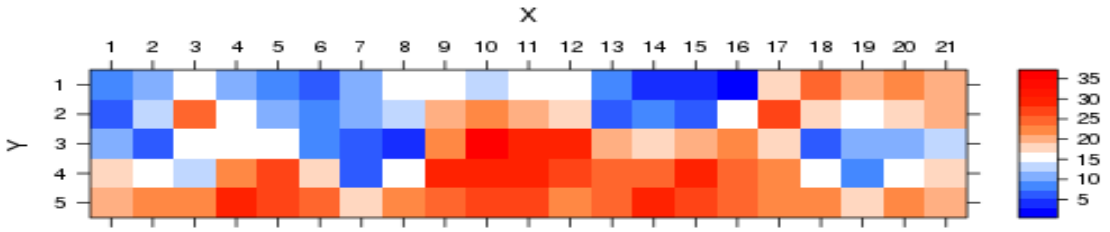
Table 1 shows the mean Equal Error Rates (EER) obtained with the SVM and Naïve Bayes classifiers when clas-




(a) Locations of the 52 channels relative to each other and relative to the two eyes (approximately).




(b) Color map showing how the discriminative power of the mean of the first ten points varied across the 52 channels (or brain regions). The red regions cover a large area relative to the blue regions, meaning that there is a good number of channels for which this feature was highly discriminative.




(c) Color map showing how the discriminative power of the standard deviation of the last ten points varied across the 52 channels (or brain regions). The blue regions cover a larger area relative to their coverage area in Figure 3(b), meaning that this feature was not as discriminative as the feature represented in Figure 3(b).

Figure 3: Illustrating the discriminative power of two features (the mean of the first ten points and the standard deviation of the last ten points) across the 52 channels. X is a measure of the horizontal distance from the top left corner of Figure 3(a) while Y is a measure of the vertical distance from the same point. Locations such as the white space between channels 1, 11, 12 and 22 (see Figure 3(a)), are represented by the mean value of $I_R$ of the four neighboring channels for continuity and clarity of the color map.

| **Classifier** | **Mean EER** | | **% Change in EER** |
|---|---|---|---|
| | **All Channels** | **Best Channels** | |
| **SVM** | 0.043 | 0.036 | 17.1 |
| **Naïve Bayes** | 0.063 | 0.046 | 28.3 |

Table 1: Comparing the mean EER of the two classification algorithms when all channels were used for classification with the mean EER obtained when only a sub-set of channels (i.e., the most discriminative channels) were used.

sification was done based on two scenarios: when all channels were used for user classification and when only the channels which exhibited the highest discriminative power in the previous classification step were used. The EER is the error rate at the threshold when the False Reject Rate (FRR) equals the False Accept Rate (FAR) and is very widely used to evaluate the performance of biometric authentication systems (e.g., see [15][17]). The EER ranges between 0 and 1 (or 0 and 100 on a percentage scale), with values close to zero pointing to a system that performs well at separating users.

When all channels were used, both classifiers had EERs of less than 7% which reduced to under 5% when the best channels were used. The reductions in EER seen when a sub-set of channels (mostly the lower channels; see Figure 3) were used confirms the benefits of our feature analysis

step (i.e., a performance boost and a lower computation overhead) and suggests that blood flow around the region just above eye-level might be the best (relative to blood flow at other regions of the head) at discriminating between users undertaking simple mathematical tasks such as addition. A more rigorous evaluation of these regions of interest and how they relate to different tasks performed by the authenticated user is part of our ongoing research. Overall, these low error rates depict the promise of fNIRS as a continuous authentication modality which could serve as extra layer of security to the traditional security mechanisms e.g., passwords.

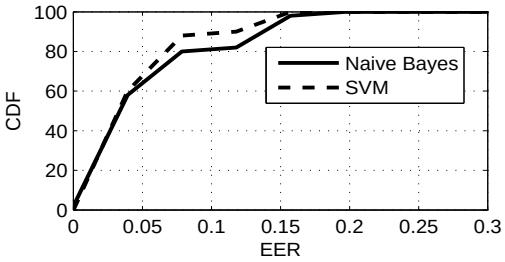
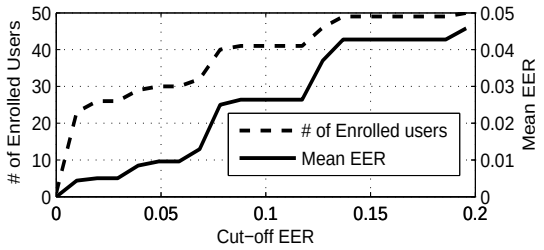



Figure 4: CDF of the EERs obtained across the population for the two classifiers.

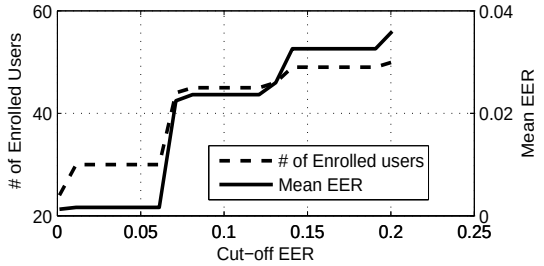
While the above described results provide insights into the mean error rates over the full population, it is interesting to also explore how each of the 50 users in our experiment performed. Figure 4 shows a CDF of the user-level EERs across the population for both classifiers. For both classifiers, over 60% of the population had EERs less than 0.05, while under 20% of the population had EERs greater than 0.1. The large proportion of users with very low EERs indicates that: (1) a significant number of users had consistent brain activity patterns over the four measurement sessions of our study, and that (2) the mean EER seen across the population could perhaps have been tremendously improved if the small group of users who for some reason (e.g., not concentrating on the tasks) had inconsistent brain activity patterns over the four sessions had been excluded prior to our authentication evaluations.

### 5.2.2 Impact of Failure-to-Enroll Policy

The second conclusion made in the previous section prompts the following question: How would the mean error rate across the population change if users who exceeded a certain threshold EER were systematically barred from enrolling onto the system? While we do not have explicit information on which users did not concentrate on the tasks as instructed, it is reasonable to assume that a carefully tuned failure-to-enroll policy would have a good chance of eliminating these kinds of users and any users who might have concentrated on the tasks but perhaps just did not have the




(a) Impact of Failure-to-enroll policy on the performance of the Naïve bayes classifier.




(b) Impact of Failure-to-enroll policy on the performance of the SVM classifier.

Figure 5: Illustrating how a failure-to-enroll policy at different thresholds affects the classifier Error Rates.

required consistency of brain activity patterns. In a real fNIRS-based authentication system, failure-to-enroll decisions would be made based on observations (e.g., EERs) made on preliminary data collected before the enrollment phase.

Figure 5 shows how a failure-to-enroll policy impacted the EERs of the two verifiers at different cut-off thresholds. Figure 5(a) shows that when all users who had an EER exceeding 0.1 were excluded from the system, the mean EER dropped from around 0.045 to just over 0.025 (an improvement of over 40%) yet about 40 users (i.e., 80% of the original population) were still able to enroll onto the system. When the cut-off EER is reduced to 0.05, the mean EER of the system reduces further to 0.01 (a change of 67% relative to the original EER) with 60% of the population able to enroll. A slightly less dramatic trend is seen with the Naïve Bayes classifier (Figure 5(b)), however the fact that barring a small number of users from enrolling onto the system significantly improves the performance of the fNIRS authentication system is still apparent.

## 6. Conclusions

In this paper, we evaluated fNIRS as a biometric authentication modality based on data collected from 50 users while they carried out simple arithmetic tasks. When we used data from all 52 channels of the Hitachi Medical's ETG4000 fNIRS device, we obtained mean EERs of 0.043 and 0.063 respectively for the SVM and Naïve Bayes clas-

sification algorithms. When we used data from a sub-set of channels having the highest individual discriminative power (as measured from the Relative mutual information metric) the mean EERs of the two classifiers respectively dropped to 0.036 and 0.043. While there is still a need to evaluate fNIRS for a wider range of mental tasks, these results suggest that fNIRS holds promise as an AA modality. A major part of our ongoing research is to carry out analysis on a wider variety of tasks and to more rigorously evaluate the dependence of authentication performance on specific brain regions.

## 7. Acknowledgment

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