EEG-based Biometric Authentication using Deep Learning

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What is EEG?

- An **Electroencephalogram (EEG)** is the electrical activity of your brain.
- Each person has a unique combination of biological brain structure and involuntary memory.
- This makes EEG **unique, universal, secure and reliable** for every individual.

Problem Statement

- Our project aims at creating a **Biometric Recognition Framework** for individuals based on their **EEG signals.**

- We aim to tackle two problems:

    - If Biometrics are **forged/stolen**, then how to generate **multiple unique** Biometrics.

    - **Limited availability** of labelled data for training a neural network.

Pros of EEG over Existing Biometrics

- Once the Biometric such as a fingerprint, an iris or a face is **stolen**, **it simply becomes useless.**

- EEG-based Biometrics can be used **again and again** to generate **infinitely unique** Biometric for **different stimuli.**

Comparison with Existing Biometrics

	Signature	**Fingerprint**	**Face**	**Iris**	**EEG**
Unique	M	H	M	H	**H**
Universal	L	M	H	H	**H**
Secure	L	H	M	M	**H**
Reliable	M	H	M	H	**H**
Permanent	M	H	M	H	**H**
Performance	M	M	L	H	**H**

One-Shot Learning

- Existing implementations use a traditional **ML/DL classification** model for identifying/authenticating a person.

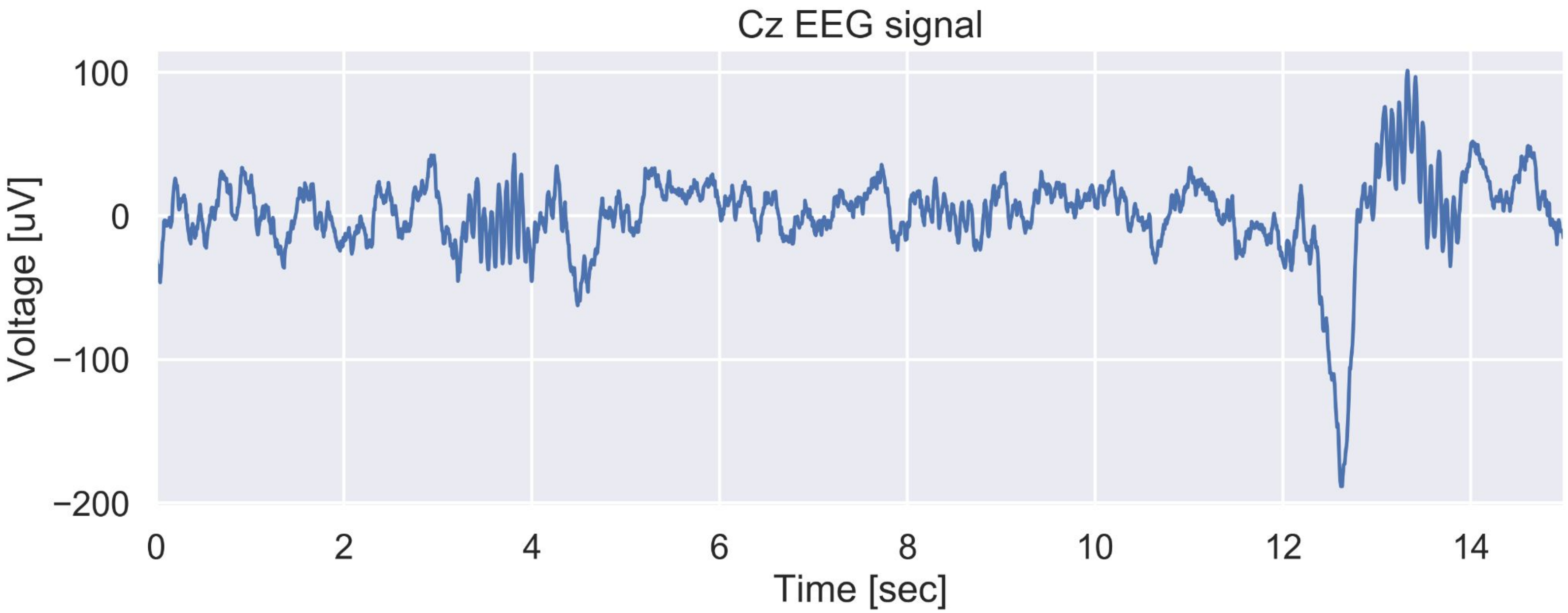
- Current approaches do not solve the **One-Shot Learning problem**.

One-Shot Learning

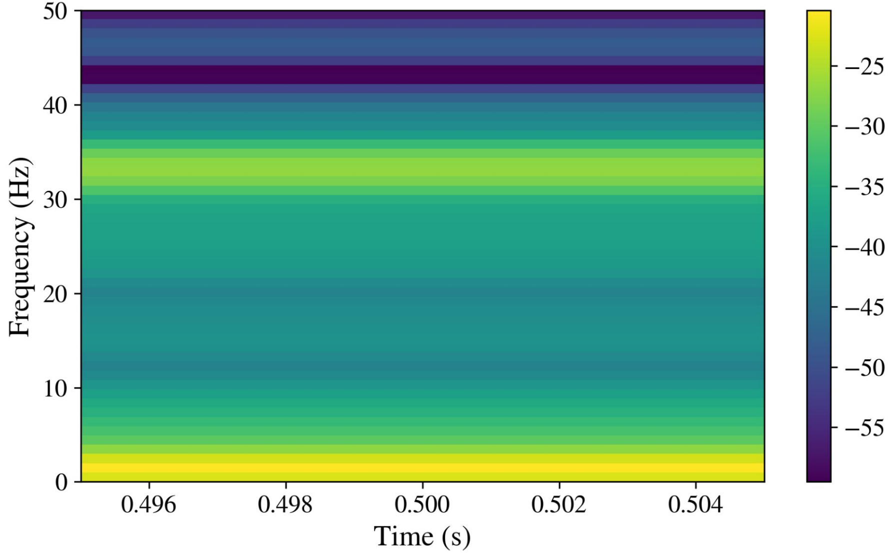
- **ML/DL Classification** algorithms require training on **hundreds or thousands** of samples/images and very large datasets.

- **One-shot Learning** aims to learn information about object categories from **one, or only a few**, training samples/images.

Representing EEG data with Spectrograms



Representing EEG data with Spectrograms



- A spectrogram is a visual way of representing the **loudness/strength** of a signal over time at various frequencies.

- X-axis represents **time**

  Y-axis represents **frequency**

  3rd dimension is **amplitude** which is color coded.

Dataset Description

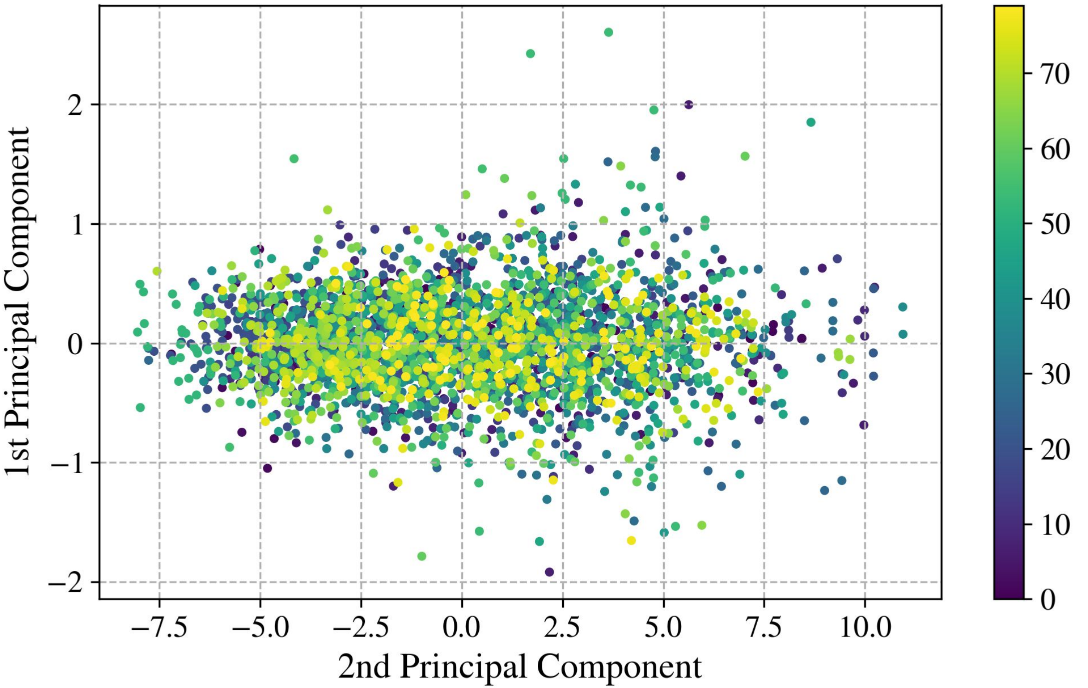
- The dataset used in this project is the publicly available **PhysioNet EEG Motor Movement/Imagery Database (EEGMMIDB).**

- The BCI2000 system was used to record **64-channel** EEG recordings of **109 subjects**, with each subject recording 14 experimental runs.

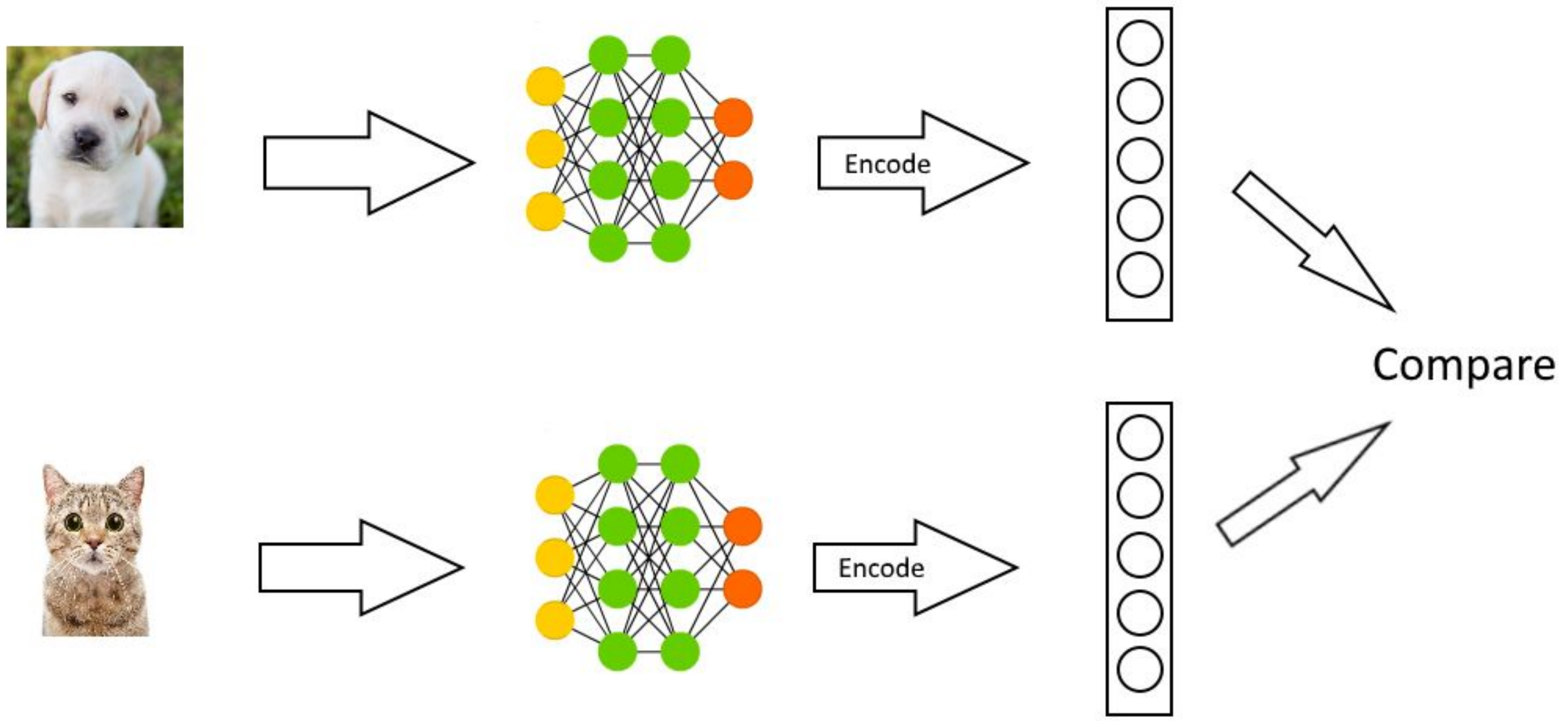
Dataset Description

- The following mental task must be completed by the subject:
    - A target can be found at the top or bottom of the screen.
    - If the target is on top, the subject imagines opening and closing both fists.
    - If the target is on the bottom, the subject imagines opening and closing both feet, until the target vanishes.
    - The subject then begins to relax.

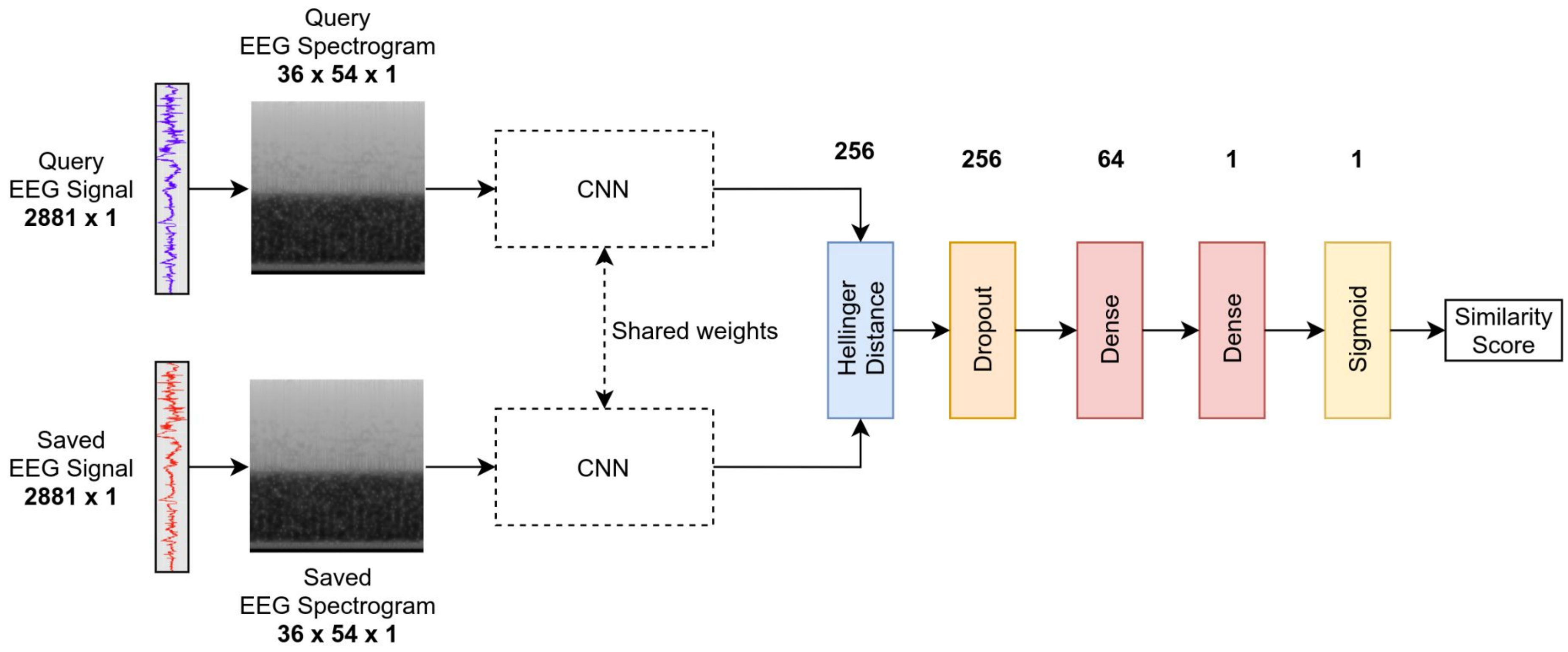
Dataset Visualization



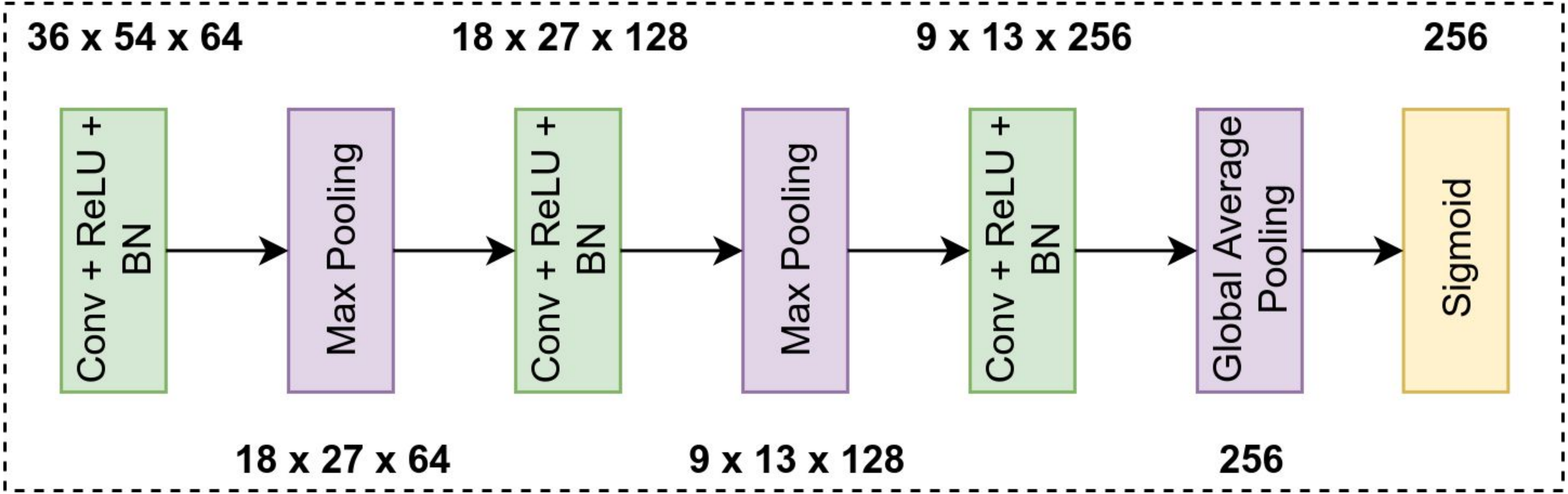
Siamese Neural Networks



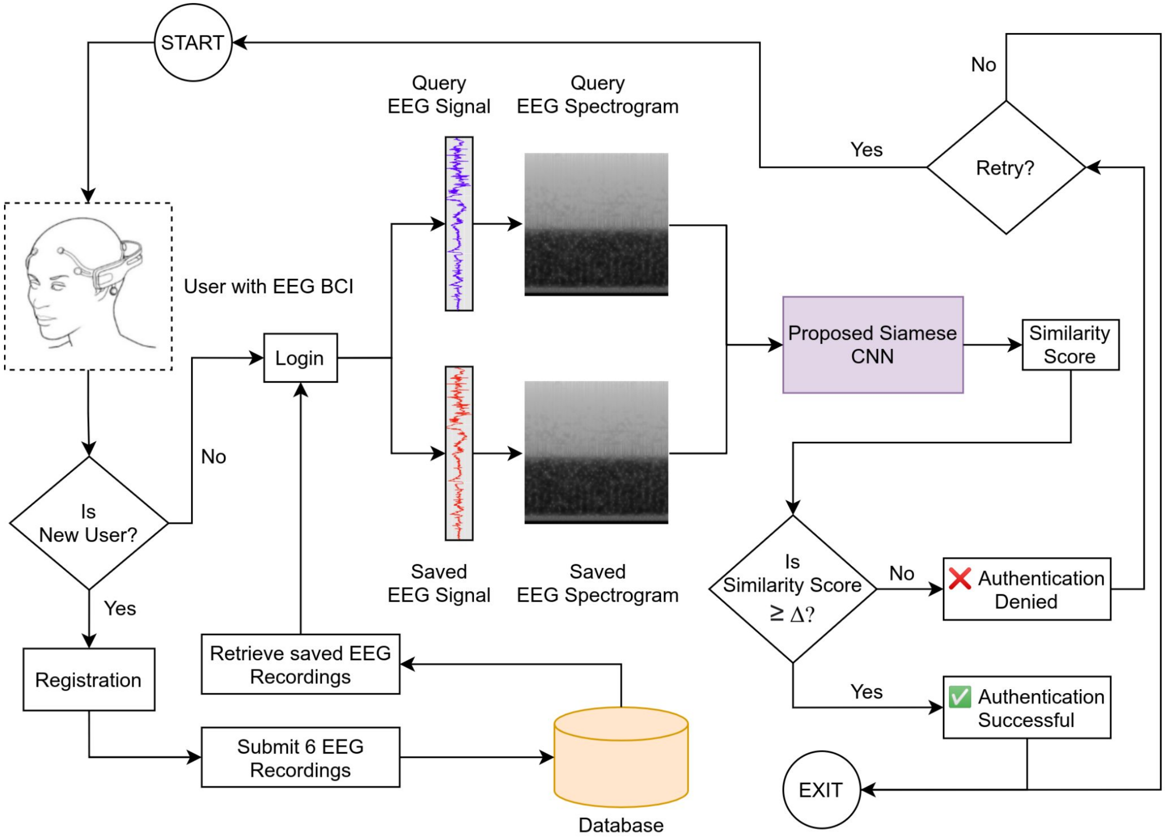
Proposed Model: SiamEEGNet



SiamEEGNet CNN Subnetwork



System Architecture



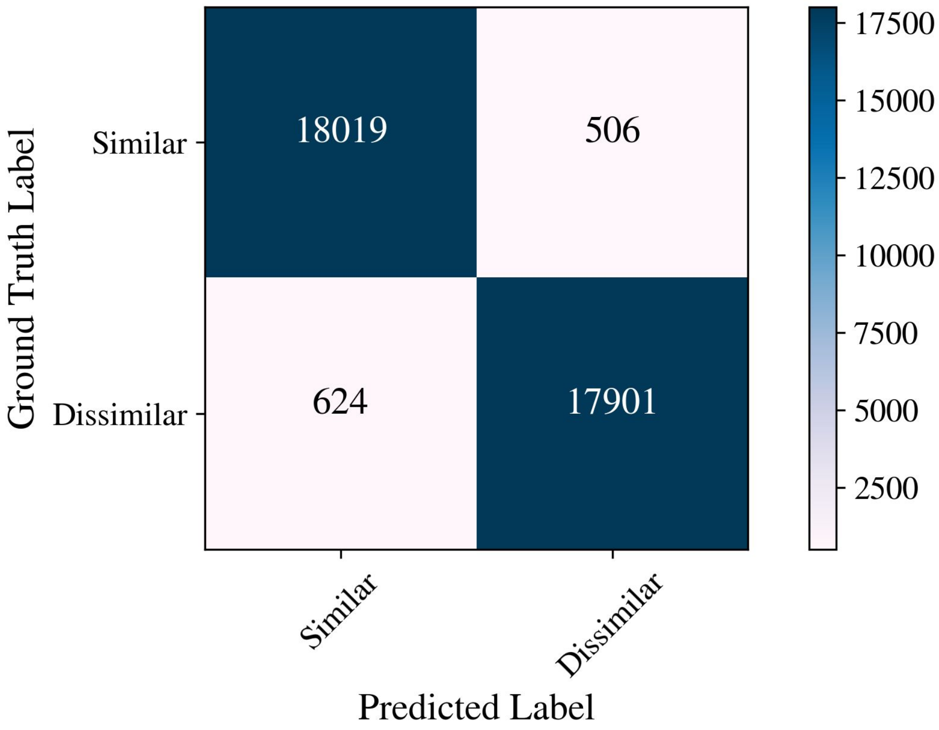
Biometric Tasks

Biometric Verification	Biometric Identification
Authenticating a user's identity by matching a submitted biometric to see if it matches a specific database template.	Locating an unknown person's name by comparing his or her live biometric samples with all templates previously stored in a system's database.
1:1 matching	1:N matching

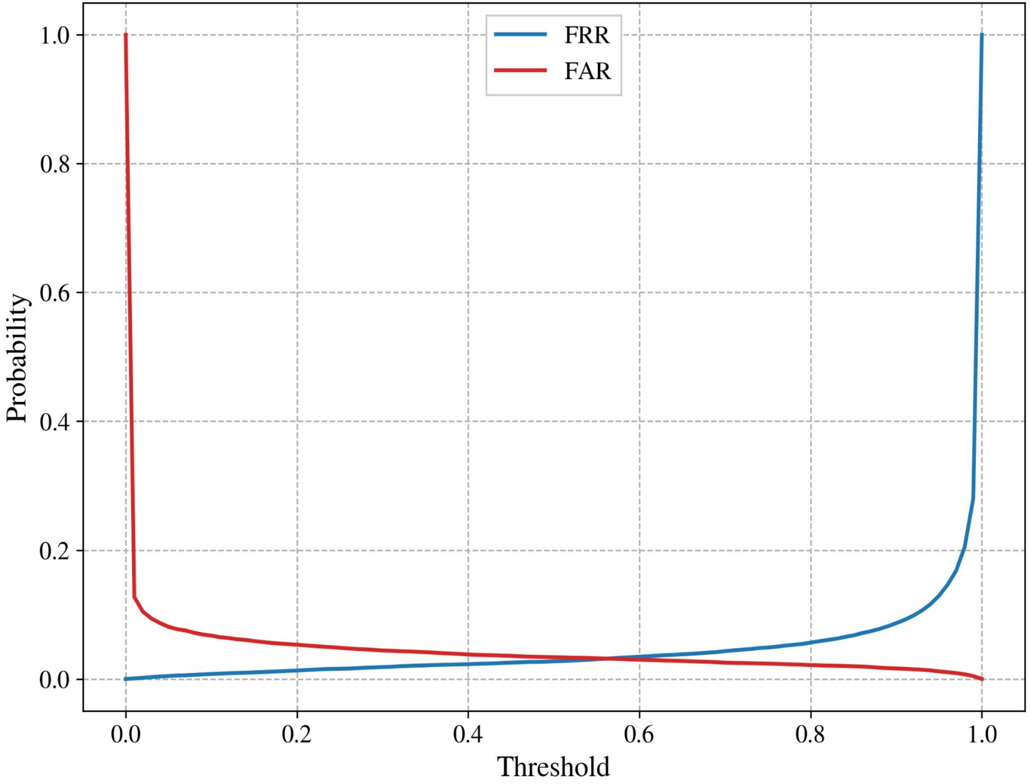
Results: Classification Report

	Precision	Recall	F1-score
Class Similar	0.97	0.97	0.97
Class Dissimilar	0.97	0.97	0.97
Accuracy	-	-	0.97
Macro avg.	0.97	0.97	0.97
Weighted Avg.	0.97	0.97	0.97

Results: Confusion Matrix



Results: FAR, FRR vs. Threshold



$$FAR = \frac{|FA|}{|IA|} \qquad FRR = \frac{|FR|}{|AA|}$$

FA: no. of false acceptances

IA: no. of attempts by an impostor

FR: no. of false rejections

AA: no. of authorized attempts

Results: EER

$$EER = FAR(T^*) = FRR(T^*)$$

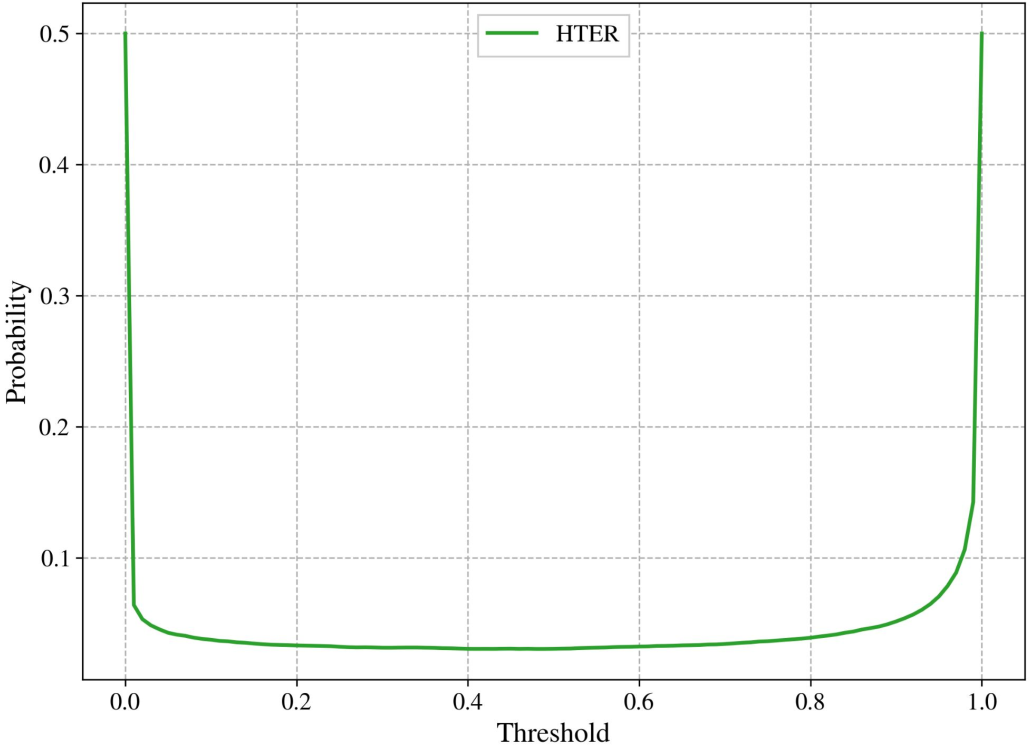
$$T^* = argmin(|FAR(T) - FRR(T)|)$$

FAR: False Acceptance Rate

FRR: False Rejection Rate

- More the EER is **near to 0**, **better is the performance** of the Biometric system.
- **SiamEEGNet** is able to obtain an EER of **0.0314** at a corresponding threshold of **0.552.**

Results: HTER vs. Threshold

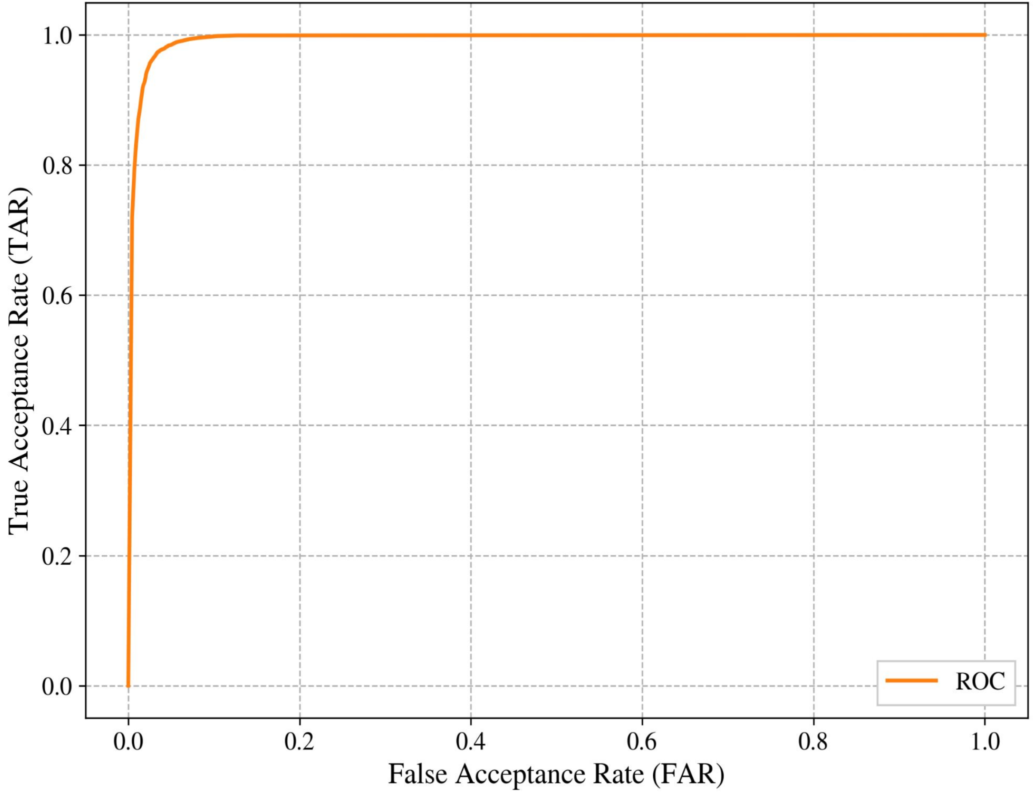


$$HTER(T) = \frac{FAR(T) + FRR(T)}{2}$$

FAR: False Acceptance Rate

FRR: False Rejection Rate

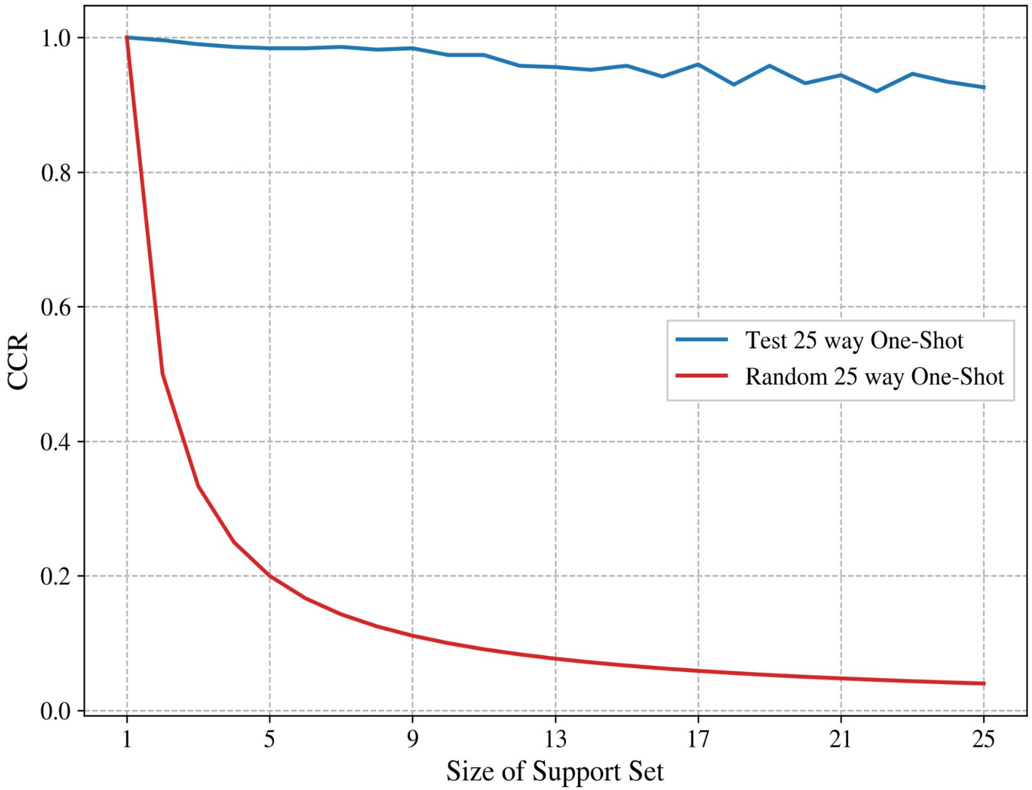
Results: ROC Curve



$$TAR = 1 - FRR$$

FRR: False Rejection Rate

Results: Average CCR for 450 runs



$$CCR = \frac{|C|}{|T|}$$

C: No. of correct classification decisions

T: No. of trials

Results: Rank-k Accuracy

$$Rank - k\ Accuracy = \frac{no.\ of\ top - k\ correctly\ authenticated\ samples}{total\ no.\ of\ test\ samples}$$

For 25 Subjects	Rank-1	Rank-5
Mean	0.972	1.0
Standard Deviation	0.062	0.0

Conclusion

- The project formulates the Biometric Recognition problem as a One-Shot Learning task allowing the proposed approach to be **applied to novel data categories** in the EEG domain without **further training** the model on **new data** which might be **sparsely available** or **costly to annotate** manually.

- The entire Deep Learning pipeline was successfully executed and tested. Based on an extensive literature survey, **no previous work** known to the best of the authors' knowledge has **adopted a One-Shot Learning approach for EEG-based Biometric Recognition.**

Future Scope

- The Contrastive loss emphasizes on more **absolute similarity** values and hence gives less attention to **inter-class and intra-class variations**. Instead we could use the **Triplet loss** and the **Triplet network** proposed by Schroff et al. and Ye et al. respectively.

- The EEG output of an individual is affected by factors such as **emotional stress, alcohol consumption and BCI sensor/device noise**. Such scenarios can be considered and further experimentation can be done.

Publications

1. Siddharth Sanghavi, Parag Vaid, Palash Rathod & Kriti Srivastava, "**SpatioTemporalNet: Improving Automated Sleep Stage Scoring with Stacked Generalization**", 2nd International Conference on Electronics and Sustainable Communication Systems (ICESC 2021). (Accepted)

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1. Gui, Qiong & Jin, Zhanpeng & Xu, Wenyao. (2015). Exploring EEGbased biometrics for user identification and authentication. 2014 IEEE Signal Processing in Medicine and Biology Symposium, IEEE SPMB 2014 Proceedings. 10.1109/SPMB.2014.7002950

2. Koch, Gregory R.. "Siamese Neural Networks for OneShot Image Recognition." (2015).

3. Hadsell, Raia & Chopra, Sumit & Lecun, Yann. (2006). Dimensionality Reduction by Learning an Invariant Mapping. 1735 1742. 10.1109/CVPR.2006.100.

4. Rui, Zhang. (2018). A Survey on Biometric Authentication: Toward Secure and Privacy Preserving Identification. IEEE Access. PP. 11.10.1109/ACCESS.2018.2889996.

5. Nieves, Orlando & Manian, Vidya. (2016). Automatic person authentication using fewer chan nel EEG motor imagery. 16. 10.1109/WAC.2016.7582945.

6. Chan, H., Kuo, P., Cheng, C., & Chen, Y. (2018). Challenges and Future Perspectives on ElectroencephalogramBased Biometrics in Person Recognition. Frontiers in Neuroinformatics,

Thank You