IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 11, Issue 4, April 2024

DOI: 10.17148/IARJSET.2024.11439

NeuroSync: Thoughts to Character ConversionThrough Deep Learning Ensemble Model

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Abstract: NeuroSync is a pioneering brain-computer interface (BCI) system designed for real-time character recognition, leveraging electroencephalography (EEG) signals to enable seamless communication and control. This paper presents the architecture, implementation, and evaluation of NeuroSync, emphasizing its potential to revolutionize human-computer interaction paradigms and empower individuals with diverse abilities. The system utilizes the BioAmp EXG pill for EEG signal acquisition, coupled with the ADS1115 analog-to-digital converter for precise digitization. A Raspberry Pi 3B+ serves as the computational hub, employing an ensemble model to classify incoming signals into eight characters (‘f’, ‘b’, ‘l’, ‘r’, ‘y’, ‘n’, ‘h’, ‘e’) each corresponding to a certain word. NeuroSync embodies a convergence of interdisciplinary expertise, drawing insights from neuroscience, machine learning, and embedded systems. NeuroSync has the capacity to enhance communication and augment human-machine interaction. This paper provides insights into the technical specifications, signal processing pipeline, machine learning architecture, and performance evaluation of NeuroSync, showcasing its potential to foster inclusive computing and improve the quality of life for individuals with disabilities.

Keywords: Brain-Computer Interface (BCI), Electroencephalography (EEG), Assistive technology, Real-time character recognition, Human-Computer Interaction (HCI)

I. INTRODUCTION

In the domain of human-computer interaction (HCI), the integration of neuroscience and technology has opened up avenues for groundbreaking solutions aimed at enhancing communication and control systems. One of the most notable advancements in this realm is the development of Brain-Computer Interfaces (BCIs), which establish direct connections between the human brain and external devices, enabling users to interact with computers or machines solely through brain activity. This fusion of neuroscience and technology has led to a paradigm shift, revolutionizing the way we perceive and engage with digital interfaces.

BCIs have a diverse range of applications, with real-time character recognition standing out as a particularly impactful advancement. This technology holds immense promise for individuals with motor disabilities, offering them a means to communicate and control devices with unprecedented ease and precision. Moreover, BCIs have the potential to redefine human-machine interaction paradigms, ushering in a future where seamless communication and control are accessible to all.

Introducing NeuroSync, a cutting-edge BCI system designed by researchers to facilitate real-time character recognition using electroencephalography (EEG) signals. The architecture of NeuroSync is meticulously crafted, leveraging off-the-shelf hardware components and advanced machine learning algorithms to create a streamlined and efficient system. Central to NeuroSync is its compact 1-channel EEG sensor, which captures electrical activity from the user's scalp, providing crucial data for analysis.

The core of NeuroSync lies in its robust ensemble model, meticulously crafted to analyze incoming EEG signals in real-time and classify them into corresponding characters, where 'f' translates to 'forward,' 'b' to 'backward,' 'l' to 'left,' 'r'to 'right,' 'y' to 'yes,' 'n' to 'no,' 'h' to 'hungry,' and 'e' to 'emergency.'

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This classification process is pivotal, as ittransforms the user's brain activity into actionable commands or textual output, facilitating seamless interaction with external devices or applications. The simplicity and effectiveness of NeuroSync's design make it a game-changer in therealm of BCIs, democratizing access to this transformative technology.

NeuroSync's versatility extends beyond traditional applications, with potential uses in fields such as gaming, virtual reality, and neurofeedback training. Its ability to decode brain signals opens doors to innovative experiences and personalized interactions, enhancing user engagement and immersion.

Furthermore, NeuroSync's user-centric design emphasizes accessibility and user experience, ensuring that individuals of varying abilities can benefit from its functionalities. This focus on inclusivity aligns with the broader goal of creating technology that empowers and enhances the lives of all users, regardless of their physical or cognitive capabilities.

The ongoing advancements in BCI technology, exemplified by NeuroSync, underscore a transformative shift towards a more symbiotic relationship between humans and machines. As these technologies continue to evolve, we can anticipate even greater strides in enhancing communication, control, and interaction paradigms, ultimately shaping a more connected and accessible digital future.

II. RELATED WORK

In recent years, the field of Brain-Computer Interface (BCI) research has witnessed a surge in interest, particularly in utilizing electroencephalography (EEG) signals for various applications. A multitude of pioneering studies have emerged, showcasing the potential of BCI technology across diverse domains.

"Think2Type: Thoughts to Text using EEG Waves" [15] presents an innovative application of BCI technology tailored to empower individuals with visual impairments. By harnessing EEG signals to capture brain activity associated with thoughts, the study introduces a solution for secure data entry, addressing privacy concerns and enhancing independence. This advancement in privacy-focused BCI applications highlights the growing importance of user-centric designs in neurotechnology.

Similarly, "Imagined Speech Classification with EEG Signals for Silent Communication: A Preliminary Investigation into Synthetic Telepathy" [25] delves into the realm of silent communication through EEG signals. The study tackles challenges related to EEG signal classification for imagined speech and proposes preprocessing techniques to mitigate noise and artifacts, paving the way for improved communication modalities. This emphasis on preprocessing techniques showcases the ongoing efforts to enhance the robustness and accuracy of BCI systems, particularly in challenging environments.

In the realm of assistive technology, "EmoWrite: A Sentiment Analysis-Based Thought to Text Conversion" [9] introduces a novel approach that combines sentiment analysis and thought-to-text conversion. This integration enables individuals with speech impairments to effectively express thoughts and emotions, offering new avenues for inclusive communication. The fusion of sentiment analysis and BCI technology represents a significant step towards personalized and expressive assistive communication solutions.

Furthermore, "Continuous Silent Speech Recognition using EEG" [7] explores the feasibility of utilizing EEG signals for continuous silent speech recognition. This study investigates the potential applications of EEG-based communication accessibility, showcasing advancements in real-time speech recognition technology. The focus on continuous speech recognition underscores the growing demand for seamless and intuitive BCI interfaces in diverse user scenarios.

Additionally, "High Accuracy Silent Speech BCI Using Compact Deep Learning Model for Edge Computing" [1] presents a compact deep learning model tailored for edge computing in silent speech BCI systems. The study highlights the importance of efficient model architectures for real-world deployment, offering insights into optimizing BCI systems for practical use. This emphasis on edge computing aligns with the trend towards decentralized and efficient computing solutions in neurotechnology research.

Moreover, "A Bimodal Deep Learning Architecture for EEG-fNIRS Decoding of Overt and Imagined Speech" [4] explores a bimodal deep learning approach for decoding EEG and functional near-infrared spectroscopy (fNIRS) signals during overt and imagined speech tasks. This study underscores the significance of multimodal data fusion in enhancing BCI performance and robustness. The integration of multiple data modalities reflects a holistic approach to BCI development, catering to diverse user needs and scenarios.

DOI: 10.17148/IARJSET.2024.11439

Collectively, these studies illustrate the diverse applications and advancements in BCI technology, showcasing its potential to revolutionize human-computer interaction and assistive communication. Each contribution offers valuable insights and methodologies, driving forward the evolving landscape of BCI research and development.

III. LITERATURE SURVEY

Sl.no	Paper	Dataset	Methodology	Remarks
1	Aditya Srivastava, Sameer Ahmed Ansari, Tanvi Shinde, Prashant Kanade and Prateek Mehta "Think2Type: Thoughts to Text using EEG Waves", International Journal of Engineering Research & Technology (IJERT), 2020	EEG motor movement/imagery database available on PhysioNet.	FFT transformation, Ensemble Deep Learning model.	However, further validation and usability testing are necessary forreal-world application.
2	K. Brigham and B. V. K. V. Kumar,"Imagined Speech Classification with EEG Signals for Silent Communication: A Preliminary Investigation into Synthetic Telepathy," 2010 4th International Conference on Bioinformatics and Biomedical Engineering 2010	EEG signals recorded from 7 volunteersubjects imagining the syllables /ba/ and /ku/.	K - Nearest Neighbors (KNN) classification algorithm	Small sample size, the lack of diversity in the subject pool, and the limited number of imagined syllables.
3	Shahid, Aisha, Imran Razaand Syed Asad Hussain. "EmoWrite: A Sentiment Analysis-Based Thought to Text Conversion." ArXiv, 2021	Four separate datasets were created, each containing words associated with a specific emotional class.	Recurrent Neural Networks (RNN)	It's vocabulary is constrained and itcurrently outputs single words. Moreover, its focus on sentiment analysis, while valuable, might notalways capture the full nuance of thought.
4	Vorontsova D, Menshikov I, Zubov A, Orlov K, Rikunov P, Zvereva E, Flitman L, Lanikin A, Sokolova A, Markov S, Bernadotte A. Silent EEG-Speech Recognition Using Convolutional and Recurrent Neural Network with 85% Accuracy of 9 Words Classification. Sensors . 2021	270 subjects recorded 8 Russian commandsand 1 pseudoword.	Convolutional and Recurrent Neural Network	Expand the dataset to include a more diverse group of participants, russian words were used which limits the population, and the accuracy rate was 85%.
5	X. Zhang, L. Yao, Q. Z. Sheng, S. S. Kanhere, T. Gu and D. Zhang, "Converting Your Thoughts	Public MI-EEG Dataset and datasetcollected in the lab.	Joint Convolutional and Recurrent NeuralNetwork, Autoencoder layer,	Further improvements can bemade by focusing ona person-independent

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	to Texts: Enabling Brain Typing via Deep Feature Learning of EEG Signals," 2018		Public MI-EEG Dataset	approach where some individuals data is used for training and others for testing.
6	P. Ghane, G. Hossain and A. Tovar, "Robust understanding of EEGpatterns in silent speech," National Aerospace and Electronics Conference (NAECON), 2015	Consists of vowels for20 subjects.	Principal Component Analysis (PCA) for Feature Extraction, Dataset consists of vowels for 20 subjects,	The dataset is limited to vowels, data of only 20 subjects were collected, and they used PCA which assumes that data is linear and can be considered as a major disadvantage.
7	Arteiro, L., Lourenço, F., Escudeiro, P., Ferreira, C. (2020). Brain-Computer Interaction and Silent Speech Recognition on Decentralized Messaging Applications. In: Stephanidis, C., Antona, M. (eds) HCI International, 2020	The EMG-UKA corpus, a collection of EMG data, was gathered using a setup with six channels.	EMG data as words using HMM or LSTM	The paper lacks a practical implementation of a messaging platform using BCI and SSR, and since it relies on a single dataset of EMG signals, it has a limited scope of diversity of use cases and data sources.
8	Vorontsova D, Menshikov I, Zubov A, Orlov K, Rikunov P, Zvereva E, Flitman L, Lanikin A, Sokolova A, Markov S, et al. Silent EEG-Speech Recognition Using Convolutional and Recurrent Neural Network with 85% Accuracy of 9 Words Classification. Sensors, 2021	EEG signals recorded from 4 male subjects in their early to mid-twenties. 3 of the subjects were non-native English speakers, and 1 was a native English speaker. Each subject was asked to silently read 30 English sentences from the USC-TIMIT database while EEG signals were recorded.	Connectionist Temporal Classification (CTC) Automatic Speech Recognition (ASR) model	The paper's decoding model suffers from small vocabulary size, subject-dependency, and lack of comparison with other methods for EEG-based silent speech recognition.
9	Ravi, Kamalakkannan & Rajkumar, R. & Raj, M.M. & Devi, S.S.. Imagined Speech Classification using EEG. Advances in Biomedical Science and Engineering. 2014	EEG signals were recorded from 13 volunteers, 10 male, and 3 female, with an average age of 21 years. The subjects were instructed to imagine the English vowels 'a', 'e', 'i', 'o', and 'u' in response to visual stimuli.	Back Propagation Neural Network.	Maximum classification accuracyof 44%, indicating room for improvement. Focusing on classifying vowels may limit generalizability of the findings to a broader range of speech sounds.

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10	Nieto, N., Peterson, V., Rufiner, H.L. et al. Thinking out loud,an open-access EEG-based BCI dataset for inner speech recognition, 2022	EEG recordings during inner speech tasks, including pronounced speech, inner speech, and visualized conditions.	Surface electroencephalograp hy system	Limited sample size, focus solely on Spanish speakers, and potential confounds due to mixing imagined and actual speech.

IV. METHODOLOGY

Imagined speech recognition represents a cutting-edge endeavor, involving the intricate process of deciphering the words or phrases that an individual envisions solely through brain signals. This pioneering task presents formidable challenges, demanding a harmonious fusion of advanced hardware and software techniques. In this project, we propose a comprehensive methodology for non-invasive imagined speech recognition utilizing electroencephalogram (EEG) signals. These signals, derived as electrical recordings from the scalp, serve as the fundamental basis for our approach.

Hardware Setup

Bio-Amp EXG Pill:
The Bio-Amp EXG Pill, renowned for its high-quality biopotential signal sensing, is integrated into our hardware setup for precise acquisition of EEG signals. By meticulously configuring the sensor, we ensure EEG signal acquisition, crucial for discerning subtle neural patterns associated with imagined speech tasks. This pill acquires data over a single channel.

ADS115 ADC:
Integrated seamlessly into our hardware setup, the ADS115 Analog-to-Digital Converter (ADC) serves as the intermediary between the EEG amplifier and digital processing unit. We meticulously set the ADC parameters, including sampling rate and resolution, to capture EEG signals with unparalleled fidelity and temporal resolution.

Raspberry Pi 3B+:
As the central processing unit of our envisioned speech recognition system, the Raspberry Pi 3B+ embodies versatility and computational prowess. Leveraging the Raspberry Pi's robust processing capabilities, we execute real-time signal processing and classification tasks with remarkable efficiency and accuracy.

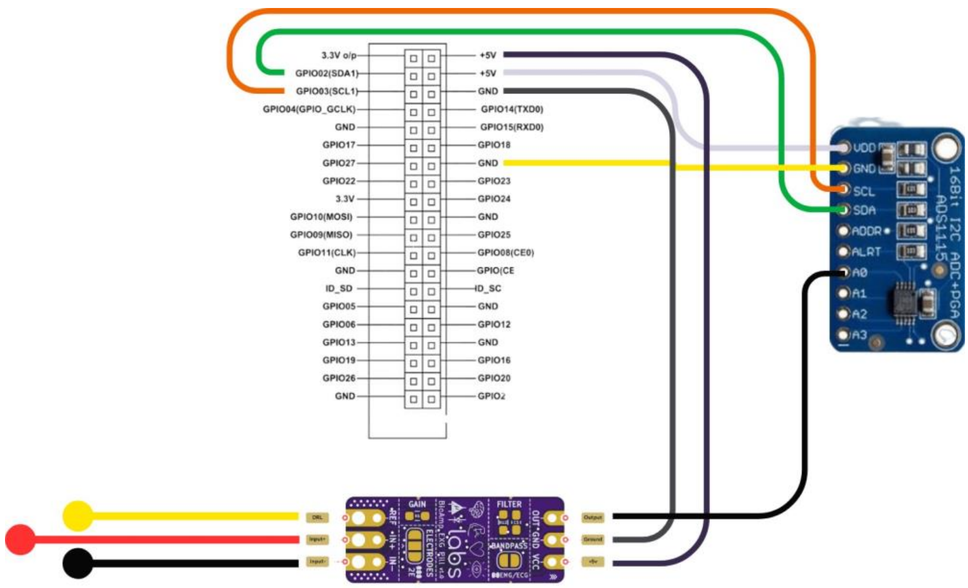

Fig 1. Circuit diagram of complete project (BioAmp EXG Pill to ADS1115 to Raspberry Pi 3B+)

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Data Collection

Signal Acquisition:
Harnessing the combined capabilities of the Bio-Amp EXG Pill and ADS115 ADC, we meticulously capture EEG signals from scalp electrodes distributed across predefined regions of interest. Ensuring precise electrode placement and optimal contact impedance, we maximize signal quality and minimize artifacts for reliable analysis.

Continuous Monitoring:
A meticulously engineered continuous monitoring system on the Raspberry Pi enables real-time acquisition and processing of EEG signals during imagined speech tasks. By establishing seamless communication channels between the EEG hardware setup and the Raspberry Pi, we ensure uninterrupted data transmission and processing.

Signal Calibration:
In recognition of individual variability in signal amplitude and characteristics, we meticulously calibrate the EEG hardware setup to accommodate diverse user profiles. Through rigorous calibration procedures, we standardize EEG signals across different users and sessions, facilitating robust and consistent analysis.

Neural Network Models

Model Architecture Design:
A cornerstone of our methodology involves the design and implementation of specialized neural network architectures tailored specifically for EEG-based imagined speech recognition. We explore a spectrum of deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), adept at extracting intricate features from EEG signals.

Training Process:
Utilizing labeled EEG data obtained from imagined speech tasks, our training process is centered around crafting bespoke neural network architectures. By developing custom CNN-LSTM and RNN models from scratch, we embrace the essence of tailored solutions. Furthermore, instead of relying solely on pre-trained models, we opt for a strategy of ensemble decision-making. This approach harnesses the collective insights of our meticulously trained models, enhancing the robustness and accuracy of our predictions.

Real-time processing pipeline

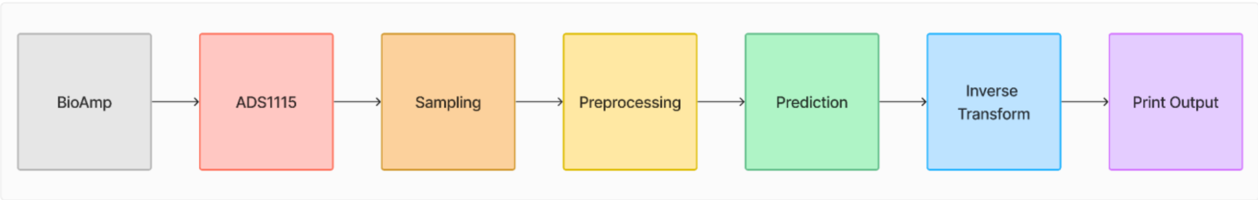

Fig 2 : Block Diagram of real-time pipeline

Data Acquisition:
EEG signals are acquired using BioAmp hardware, ensuring high-fidelity data capture. Analog signals undergo conversion to digital format through Analog-to-Digital Converters (ADCs) integrated within the ADS chipset. This process ensures compatibility with digital processing techniques.

Preprocessing:
Standardization: The acquired EEG signals undergo standardization to normalize data distribution and mitigate the effects of varying scales across different channels.
Min-Max Scaling: Following standardization, min-max scaling is applied to the EEG data, transforming it to a predefined range, typically [0, 1]. This scaling facilitates improved convergence during model training and enhances the interpretability of feature values.

Model Development:
Custom CNN-LSTM Architecture: A bespoke Convolutional Neural Network (CNN) combined with Long Short-Term Memory (LSTM) units is designed and trained to extract spatial features and capture temporal dependencies within the EEG signals, respectively.

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RNN Model Construction: Additionally, a Recurrent Neural Network (RNN) is implemented to capture sequential patterns inherent in the EEG data. The RNN model is trained to effectively encode the temporal dynamics of the signals.

Ensemble Learning:
Ensemble Construction: Predictions from both the CNN-LSTM and RNN models are aggregated using an ensemble approach. This technique combines the diverse predictions of individual models to yield a more robust and accurate final prediction.

Ensemble Decision Making: By leveraging the collective insights of multiple models, the ensemble approach enhances the overall predictive performance, thereby increasing the reliability of character predictions derivedfrom EEG signals.

Character Prediction and Real-Time Application:
Final Prediction: The ensemble model is deployed to predict the character associated with the processed EEG signals by applying inverse transform from label encoder.

Real-Time Interface: The predicted characters can be utilized in real-time applications, facilitating communication or control interfaces based on imagined speech tasks. This enables seamless integration of EEG-based character prediction into practical scenarios for enhanced user interaction and accessibility.

V. RESULT

The NeuroSync system's performance was evaluated using a machine learning technique for robust assessment. The accuracy score, a common metric for classification models, reflects the proportion of correctly classified characters. In this case, the NeuroSync system achieved an overall accuracy of 42.5%. However, accuracy alone does not provide a complete picture of the model's performance. The confusion matrix provides a more detailed breakdown of the model's predictions. Each row of the matrix represents the instances in an actual class, while each column represents the instances in a predicted class. Thus, a perfect model would havenon-zero diagonals and zeroes everywhere else.

Analyzing the confusion matrix of the NeuroSync model reveals interesting insights. The model performed well in classifying characters 'b', 'e', and 'h', achieving high true positive rates for these characters. It also showed moderate performance for characters 'f', 'r', and 'y'. However, it struggled significantly in predicting 'l', with a noticeable number of misclassifications.

To further assess the model's performance, additional metrics such as precision, recall, and the F1 score were calculated. Precision measures the ratio of true positives to the total number of positive predictions, indicating the accuracy of the positive predictions. Recall, on the other hand, measures the ratio of true positives to the total number of actual positives, indicating the model's ability to capture all positive instances. The F1 score, which is the harmonic mean of precision and recall, provides a balanced assessment of the model's performance across different classes. In the case of NeuroSync, precision, recall, and the F1 score varied depending on the character being classified. Characters with higher precision scores indicate a lower false-positive rate, while characters with higher recall scores indicate a lower false-negative rate. The F1 score considers both false positives and false negatives, offering a comprehensive evaluation of the model's predictive capabilities.

In the frontend interface of the NeuroSync system built using Streamlit, the focus is on user-friendly interaction and intuitive controls. The interface seamlessly integrates with the predictive capabilities of the system, offering a straightforward and accessible user experience.

The primary functionality revolves around converting predicted characters into meaningful words associated with them. For example, when the system predicts 'e,' it translates it to 'emergency'; 'h' becomes 'hungry'; 'y' becomes 'yes'; 'n' becomes 'no'; 'f' becomes 'forward'; 'b' becomes 'backward'; 'l' becomes 'left,' and 'r' becomes 'right.' This conversion adds a layer of clarity and usability to the predictions, making it easier for users to understand and utilize the output.

The interface also features five essential buttons to control the prediction process and manipulate the text output: Start Prediction, Stop Prediction, Add Space, Backspace and Clear. These buttons offer essential functionalities for users to interact with the system effectively. Whether starting or stopping predictions, managing text output with spaces and corrections, or clearing the interface for a fresh start, the frontend design prioritizes simplicity, functionality, and user control. Such a user-centric approach enhances the overall usability and accessibility of the NeuroSync system, empowering users to leverage BCI technology with ease and efficiency.

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While the results of this study indicate the potential of the NeuroSync system for real-time character recognition using EEG signals, it's important to note that the current accuracy falls short of perfection. Further research and refinement of the model, possibly through feature engineering, data augmentation, or model optimization techniques, are necessary to improve its performance and reliability in practical applications.

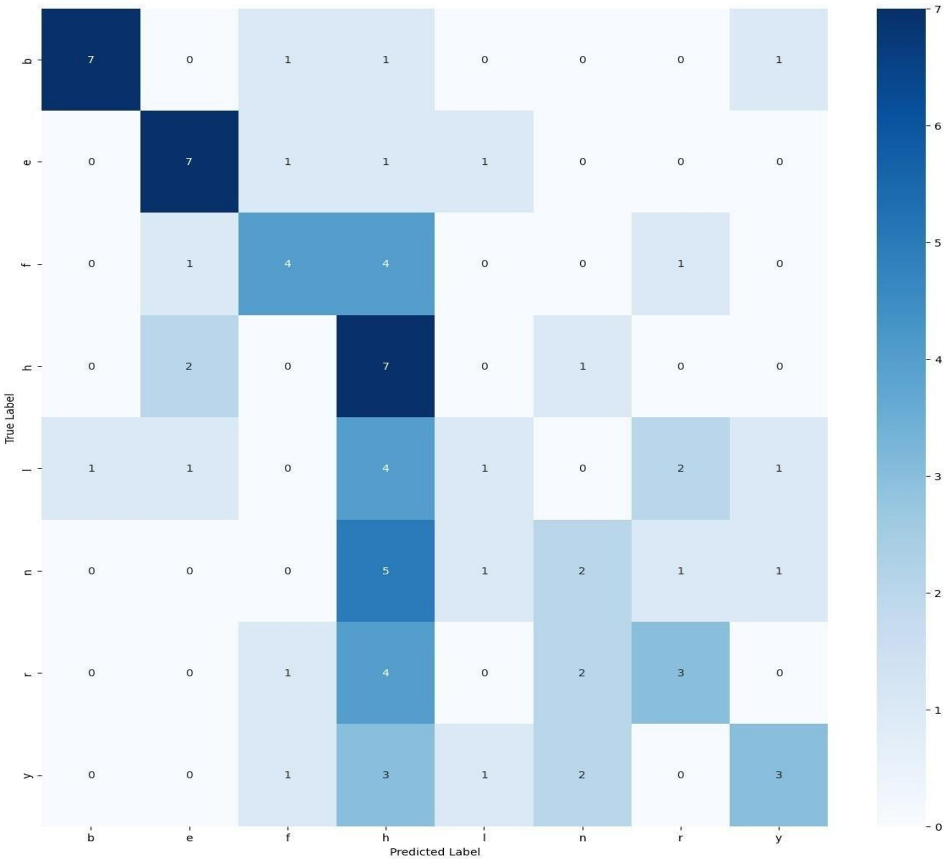

Fig 3 : Confusion Matrix of all 8 classes

Accuracy Score : 0.425

	precision	recall	f1-score	support
b	0.88	0.70	0.78	10
e	0.64	0.70	0.67	10
f	0.50	0.40	0.44	10
h	0.24	0.70	0.36	10
l	0.25	0.10	0.14	10
n	0.29	0.20	0.24	10
r	0.43	0.30	0.35	10
y	0.50	0.30	0.37	10
accuracy			0.42	80
macro avg	0.46	0.42	0.42	80
weighted avg	0.46	0.42	0.42	80

Fig 4 : Classification report of testing run

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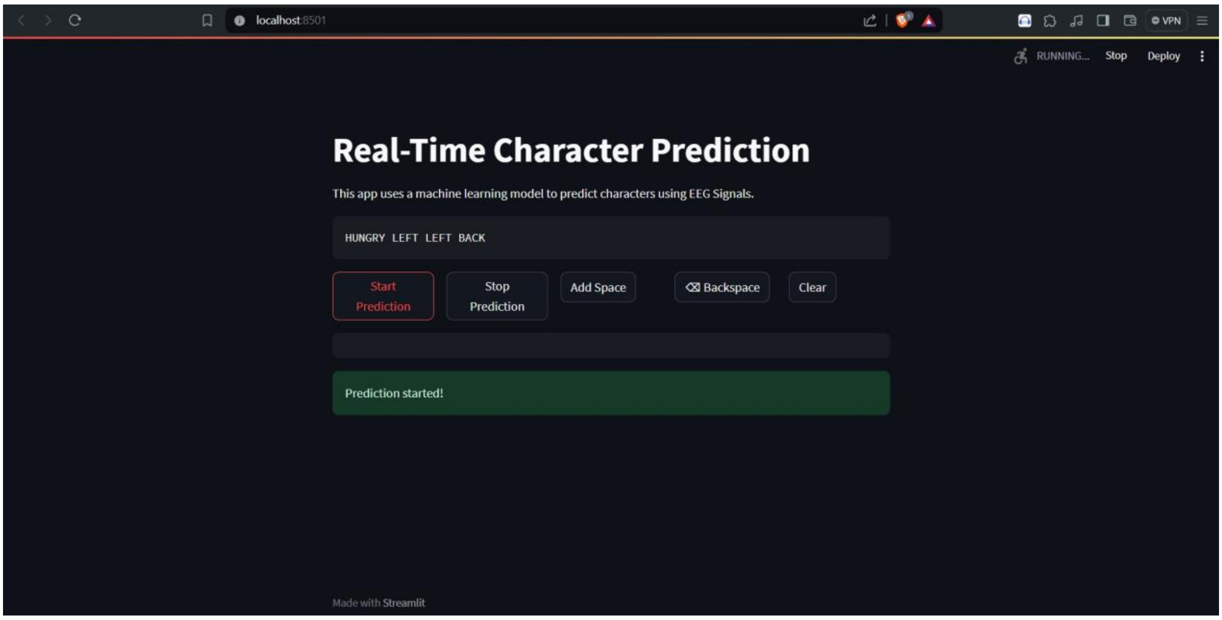

Fig 5 : User Interface

VI. ACKNOWLEDGEMENT

The team extends their sincere appreciation to Dr. Vijayalaxmi Mekali for her invaluable and constructive input throughout the planning and development phases of the project. Her expertise and guidance have been instrumental in shaping the project's direction and ensuring its success. The team is truly grateful for Dr. Mekali's generous dedication of time and commitment to excellence.

Furthermore, the team expresses gratitude to the esteemed professors of KSIT for their unwavering support and encouragement. Their mentorship and insights have been pivotal in refining the project's objectives and methodologies. The team acknowledges the professors' contributions to fostering a conducive learning environment and fostering a culture of innovation and excellence. The team also recognizes and thanks all individuals, colleagues, and stakeholders who have contributed to the project's progress and success. Their collective efforts and collaboration have been essential in achieving milestones and advancing the field of brain-computer interface technology. The team looks forward to continued collaboration and growth in future endeavors.

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