

Confusion Level Detection using EEG Signal Analysis

Shouvik Ghosh



Department of Computer Science and Engineering
National Institute of Technology Rourkela

Confusion Level Detection using EEG Signal Analysis

Dissertation submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Technology

in

Computer Science and Engineering

by

Shouvik Ghosh

(Roll Number: 120CS0154)

based on research carried out

under the supervision of

Dr. Anup Nandy



June, 2024

Department of Computer Science and Engineering
National Institute of Technology Rourkela



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Department of Computer Science and Engineering
National Institute of Technology Rourkela

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This is to certify that the work presented in the dissertation entitled *Confusion Level Detection using EEG Signal Analysis* submitted by *Showvik Ghosh*, Roll Number 120CS0154, is a record of original research carried out by him under my supervision and guidance in partial fulfillment of the requirements of the degree of *Bachelor of Technology in Computer Science and Engineering*. Neither this dissertation nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

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I, *Shouvik Ghosh*, Roll Number *120CS0154* hereby declare that this dissertation entitled *Confusion Level Detection using EEG Signal Analysis* presents my original work carried out as a undergraduate student of NIT Rourkela and, to the best of my knowledge, contains no material previously published or written by another person, nor any material presented by me for the award of any degree or diploma of NIT Rourkela or any other institution. Any contribution made to this research by others, with whom I have worked at NIT Rourkela or elsewhere, is explicitly acknowledged in the dissertation. Works of other authors cited in this dissertation have been duly acknowledged under the sections “Reference” or “Bibliography”. I have also submitted my original research records to the scrutiny committee for evaluation of my dissertation.

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Acknowledgment

The journey of completing this thesis on "Confusion Level Detection using EEG Signal Analysis" has been an enriching and transformative experience. Reflecting on my time spent on this research, I am filled with a sense of accomplishment and gratitude. The path was fraught with challenges and moments of doubt, but it was also marked by significant learning, growth, and numerous breakthroughs that have shaped my academic career.

First and foremost, I would like to express my heartfelt gratitude to my esteemed supervisor, Prof. Anup Nandy. His unwavering support, insightful guidance, and constant encouragement have been invaluable throughout this research journey. Prof. Nandy's profound knowledge and expertise have deeply influenced my work, and his patience and dedication have inspired me to push my boundaries and strive for excellence.

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June 28, 2024
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Shouvik Ghosh
Roll Number: 120CS0154

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Abstract

There are several fields, including education, healthcare, and human-computer interaction, where it is crucial to be able to accurately assess someone's cognitive state, particularly how confused they are. The effectiveness of electroencephalogram (EEG) signal processing for the detection and quantification of levels of astonishment is thoroughly evaluated in this work. In our fastpaced, information-driven culture, understanding and analyzing confusion has enormous ramifications for decision-making processes in education, healthcare, and human-computer interaction. Because it offers a non-invasive means to evaluate mental states and emotional responses, EEG is a viable approach for studying confusion. More research is needed to learn how to recognize confusion in learning and what EEG signals indicate its existence because the study of confusion in learning is still in its early stages. EEG data provide a clear window into cognitive processes and essential information about the electrical activity of the brain. Even though it is unpleasant, the learner must understand deep learning in order to participate in it. This study's categorization phase extensively utilizes machine learning methods. Furthermore, we find that the primary element for identifying brain confusion in the EEG signal is the gamma 1 wave. Heng Cui et al. claim that by suggesting a data-driven strategy for identifying and quantifying the level of perplexity via EEG signal analysis, this study initiative closes a large understanding gap in cognitive states. By enhancing our capacity to track cognitive states, this study advances the larger goal of enhancing human-computer interaction, education, and healthcare procedures.

Keywords: Human-computer interaction, gamma 1 wave, machine learning, electrical activity, and EEG (electroencephalogram).

Chapter 1 (Introduction)

1.1 Introduction to Confusion Level Detection using EEG Signal

In a time of instantaneous decision-making, it is crucial to comprehend and effectively control cognitive states like confusion. This study proposal explores the topic of "Confusion Level Detection" using electroencephalogram (EEG) signal analysis. Our work tries to answer a critical question: Can we reliably identify and measure levels of perplexity in individuals based on their brainwave patterns? using cutting-edge signal processing techniques and the precision of EEG equipment. The results of this study have important implications for a variety of sectors, including human-computer interaction, education, and healthcare. Research on the subject is still in its early stages[1], and more needs to be learned about confusion in learning and what EEG signals point to its existence.

Our research intends to provide vital new views on the potential for specialized therapies and improved decision-making in situations where confusion is a significant component, in addition to advancing our understanding of the cognitive mechanisms generating confusion. Confusion is unpleasant, yet it is necessary for the learner to comprehend profound learning[3]. This study's categorization phase extensively utilizes machine learning methods. EEG data can reveal a person's cognitive state, including moments of confusion.

By analyzing EEG data in real-time, it is possible to develop algorithms and models that can precisely identify and quantify levels of confusion. It is uncertain if a pupil finds the accuracy of 73.3 percent [2] confusing. Furthermore, we find that the primary element for identifying brain confusion in the EEG signal is the gamma 1 wave. An effective tool for assessing mental processes and emotional states is EEG, a non-invasive neuroimaging technique. This technique records the electrical activity of the brain using a number of electrodes placed on the scalp. This study fills a significant knowledge vacuum in cognitive states by proposing a data-driven approach for identifying and quantifying levels of perplexity using EEG signal analysis[4].

By enhancing our capacity to track cognitive states, this study advances the larger goal of enhancing human-computer interaction, education, and healthcare procedures. In the parts that follow, we will go over our study goals, methodology, and anticipated contributions to the scientific community in order to shed light on the enigma of perplexity and create innovative strategies for its identification and control.

1.2 Motivation

Enhancing Learning Outcomes

Real-time detection of confusion can transform educational environments by providing immediate feedback to instructors, enabling personalized learning interventions, and improving overall learning outcomes.

Improving Patient Care

In clinical settings, early detection of confusion can aid in the management of cognitive disorders, facilitate timely interventions, and improve patient monitoring, particularly for conditions like dementia or delirium.

Advancing Human-Computer Interaction

Understanding user confusion through EEG signals can lead to the development of more intuitive and adaptive user interfaces, enhancing user experience and reducing frustration in software applications.

Contribution to Cognitive Research

This research can provide deeper insights into the neural correlates of confusion, contributing to the broader field of cognitive neuroscience and helping to unravel the complexities of human cognition.

1.3 Research Problems

Measurement of Bewilderment Level: Determining objective, quantifiable metrics for differentiating between various levels of confusion is one of the main research challenges in the subject of confusion level detection. Currently, it is common to rely on subjective self-reporting and behavioral observations, which might be incorrect. The difficulty lies in developing EEGbased biomarkers or patterns that precisely correlate with various degrees of perplexity, allowing researchers to evaluate and categorize people's cognitive states without bias.

Intervention and Real-Time Detection: Creating real-time confusion detection algorithms is a crucial research issue. Existing EEG signal analysis techniques frequently involve postprocessing and offline analysis, which restricts their use in situations requiring instant action, including educational settings or surroundings where safety is at risk. Researchers must tackle the problem of spotting confusion as it happens so that prompt interventions or corrections can be made to enhance learning or decision-making outcomes.

Personal differences and generalizations: Because human brain activity differs greatly from person to person, it is extremely difficult to create an all-encompassing model for determining the level of bewilderment using EEG readings. Researchers must address the problem of individual variability and figure out how to develop models that can be used to a variety of groups while still delivering precise evaluations of users' levels of bewilderment. To address this issue and assure the stability of detection models, novel feature selection, machine learning, and data augmentation techniques are needed.

1.4 Research Objectives

EEG-Based Confusion Detection Model Development: The main goal is to create and refine a reliable EEG-based model for identifying various degrees of perplexity. This model should examine EEG data and accurately categorize people into different stages of bewilderment using advanced signal processing techniques and machine learning algorithms.

Monitoring Confusion in Real Time: The objective of the research is to develop a real-time EEG-based confusion monitoring system to enable practical applications in real-world circumstances. This system ought to give quick feedback on a person's cognitive condition, enabling quick interventions or corrections when confusion is found.

Biomarker identification in the EEG: Identify and research the exact EEG biomarkers or patterns connected to different levels of bewilderment. In order to achieve this goal, detailed EEG analysis must be performed in order to identify the neural signatures that distinguish various degrees of perplexity and could potentially yield new insights into the underlying cognitive processes.

1.5 Summery

The research project on confusion level detection using EEG signals aims to enhance educational outcomes, improve patient care, and advance human-computer interaction. By leveraging non-invasive EEG technology, this research can provide real-time insights into users' cognitive states, enabling personalized interventions in educational settings, timely management of cognitive disorders in healthcare, and development of more intuitive user interfaces. Additionally, it contributes to the understanding of neural correlates of confusion, enriching the field of cognitive neuroscience.

Chapter 2

Confusion Level Detection

2.1 Literature Review

1. Researchers Yun Zhou, Tao Xu, Shiqian Li, and Shaoqi Li[3] investigated the prospect of utilizing EEG to identify confusion during learning in their research paper, "Confusion State Induction and EEG-based Detection in Learning." 16 participants took part in the experiment the authors ran. As they worked through a series of cognitive exercises, the participants' EEG data was being captured. With a classification accuracy of 78%, the system was able to classify the EEG data.
2. The authors used a collection of EEG data acquired from 10 people while they were watching educational movies in their research paper, "Classification of Confusion Level Using EEG Data and Artificial Neural Networks," by Claire Receli M. Reosa, Argel A. Bandala, and Ryan Rhay P. Vicerra[5]. After watching each video, the participants were asked to rate how confused they were. The EEG data could be divided into three levels of perplexity with an accuracy of 86 percent using the top-performing ANN model.

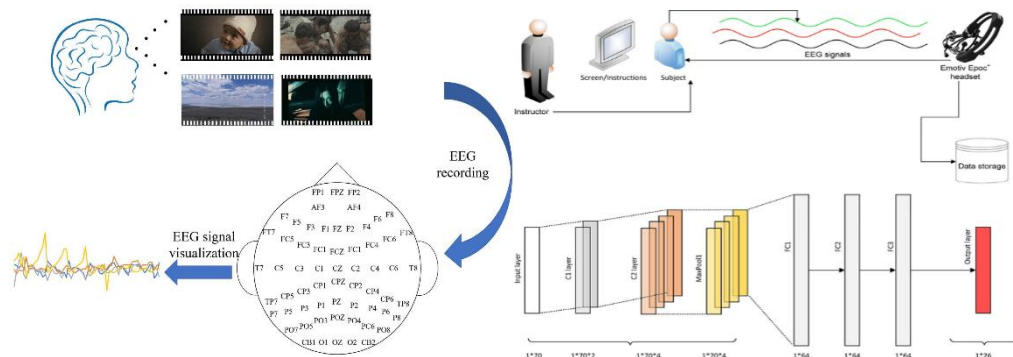
3. EEG data was gathered from 90 individuals while they watched emotional films for the work "EEG-Based Subject-Independent Emotion Recognition Using Gated Recurrent Unit and Minimum Class Confusion" by Heng Cui, Aiping Liu, Xu Zhang, Xiang Chen, Jun Liu, and Xun Chen[4]. After watching each film, the participants were asked to score their feelings. The EEG data was then divided into six categories using a gated recurrent unit (GRU) neural network, according to the authors. A subject-independent emotion recognition accuracy of 78.2 percent was attained using the suggested strategy.
4. Electroencephalogram (EEG) signals from students taking an online course were collected for the study "Electroencephalogram Signals for Detecting Confused Students in Online Education Platforms with Probability-Based Features" by Talal Daghriri, Furqan Rustam, Wajdi Aljedaani, Abdullateef H. Bashiri, and Imran Ashraf[6]. The authors evaluated their suggested methodology on this dataset. The findings demonstrated that the suggested method had a 97.2 percent accuracy rate in identifying students who were puzzled.

2.2 Methodology

Data Collection:

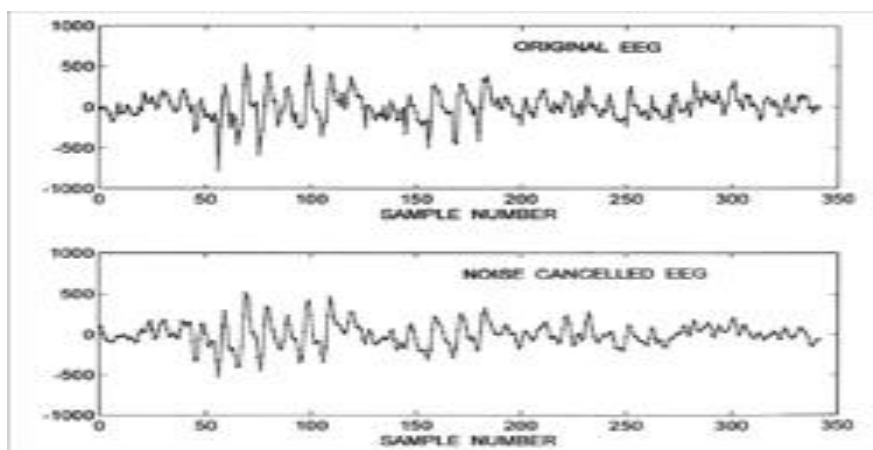
- **Recruitment of Participants:** To ensure the generalizability of findings, gather a varied group of individuals who reflect various age groups, genders, and cognitive backgrounds.
- **Aware Consent:** Obtain the informed consent of every participant by outlining the study's goals, the EEG data collection procedure, and the privacy protections.
- **Data Acquisition for EEG:** Utilizing a top-notch EEG headset will help you ensure optimal electrode placement, reduce noise, and artifacts when collecting EEG data.

- **Creating confusion:** Create activities or situations for experiments that cause varying degrees of bewilderment while continuously observing the EEG signals from the participants.



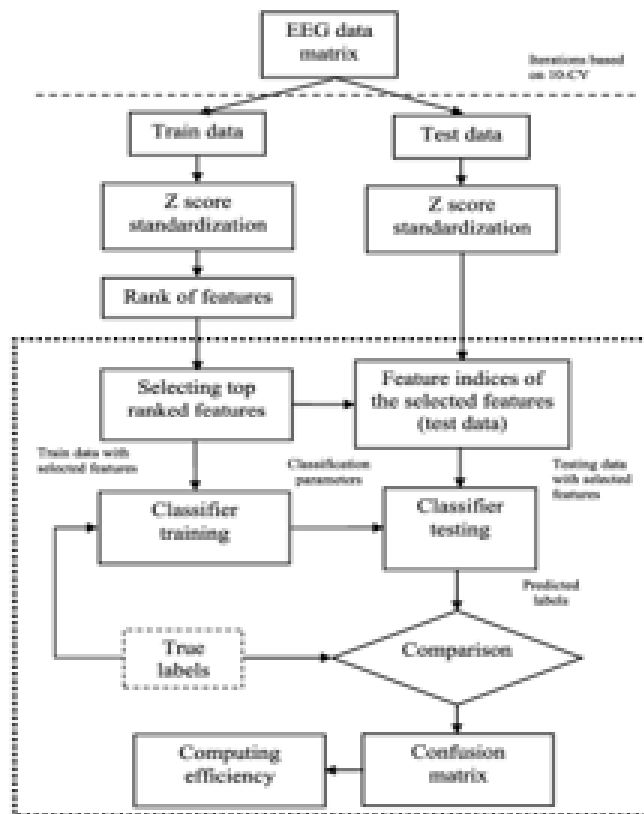
Data Preprocessing:

- **Noise Reduction:** Use preprocessing strategies to reduce noise and ensure the accuracy of EEG data, such as filtering and artifact removal.
- **Feature Extraction:** To identify the brain patterns connected to levels of bewilderment, extract pertinent elements from EEG signals, such as power spectral density, coherence, and event-related potentials.



Model Development:

- **Machine Learning Algorithms:** Create a classification model that can discriminate between mild, moderate, and severe levels of confusion using machine learning techniques (such as deep learning and support vector machines).
- **Cross-Validation:** Use cross-validation methods to evaluate model performance and guarantee generalizability across various datasets.



Data interpretation and analysis:

- Identify distinct biomarkers or brain patterns connected to various degrees of perplexity by analyzing EEG data.
- Analyze the findings to learn more about the cognitive mechanisms generating confusion.

Dissemination of the Report:

- Create a thorough report with the research's findings, methods, findings, and conclusions.
- To benefit the scientific community, disseminate the study through papers, talks, and conferences.

2.3 Research Approach

Preliminary research:

- Conduct a thorough investigation of the material already in existence on EEG signal analysis and confusion identification.
- Identify research gaps and identify potential EEG-based biomarkers connected to levels of bewilderment.

Designing an experiment:

- Create an experimental plan that is structured and includes scenarios or tasks that are intended to cause participants to experience various degrees of perplexity.
- Make sure the experimental design is morally sound, taking participant safety and well-being into account.

Data Collection:

- To ensure the generalizability of the results, gather a broad sample of people.
- All participants must give their informed consent before any EEG data is collected.
- Use an excellent EEG headset to record brainwave information throughout the tasks that cause disorientation.

Data Preprocessing:

- Use exacting data pretreatment methods, such as signal normalization, artifact removal, and noise reduction.
- Extract pertinent EEG variables, such as power spectral density, event-related potentials, and connectivity metrics, which may be used as markers of perplexity.

Model construction

- Build a classification model for confusion detection using cutting-edge machine learning techniques, including, if applicable, deep learning architectures.
- Utilize labeled EEG data corresponding to various degrees of perplexity to train the model.

- Use cross-validation techniques to assess model performance and adjust hyperparameters.

Data interpretation and analysis:

- Identify distinct biomarkers or brain patterns connected to various degrees of perplexity by analyzing EEG data.
- Interpret findings to learn more about the cognitive mechanisms underlying confusion.

Dissemination and Reporting:

- assemble study findings into a thorough report that includes methodology, outcomes, and consequences.
- Publishing, giving talks at conferences, and other means of disseminating research findings will help the scientific community.

2.4 Expected Contributions

1. Increasing scientific understanding

- By discovering EEG-based biomarkers and brain patterns linked to various levels of bewilderment, the study is anticipated to advance our understanding of confusion as a cognitive state.

2. Tool for Objective Measurement

- By replacing or enhancing subjective self-reporting and behavioral observations with an innovative and objective measurement instrument, the creation of an EEG based model for confusion level detection is able to detect levels of confusion.

3. Real-time observation and action

- By developing a real-time EEG-based system, it is now possible to monitor circumstances where confusion can affect a person's ability to make decisions or learn.

4. Human-Computer Interaction:

- By enabling systems to adjust in real-time to users' cognitive states, the research could enhance human-computer interaction and result in a more smooth and effective user experience.

5. Applications that Cut Across Disciplines

- Beyond the area of the original research, the conclusions and technologies may have uses in a variety of domains, including psychology, neuroscience, artificial intelligence, and more.

6. Real-world Application:

- By bridging the gap between theoretical research and practical applications, the suggested method intends to make EEG-based confusion detection a workable and useful tool in a variety of real-world situations.

7. Iterative Development

- The project aims to develop a system that continuously evolves and improves, remaining relevant and efficient over time by stressing iterative improvement based on user feedback and real-world data.

8. Support for the Scientific Community:

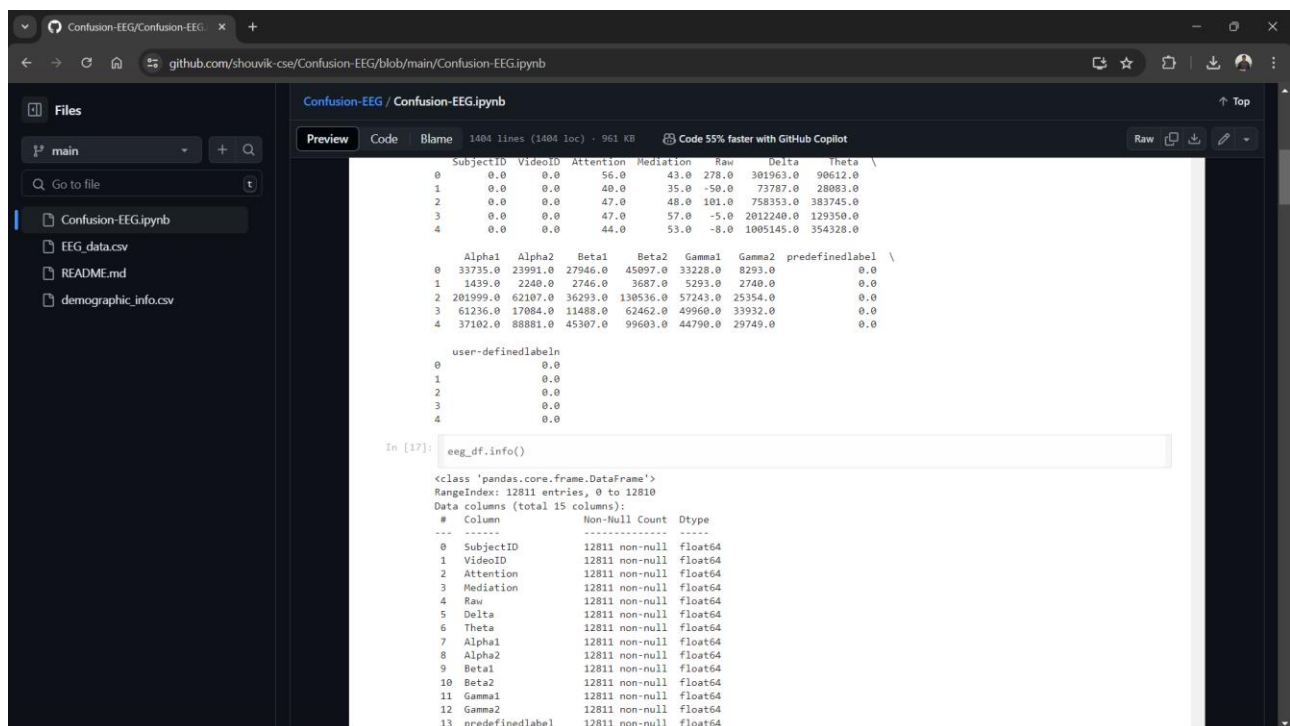
- The distribution of study findings via papers and talks will offer the scientific community helpful approaches and insights, encouraging more research and innovation in the subject.

Chapter 3

Implementation and Result

Load the EEG data from the CSV file into a DataFrame and then print the first few rows to get an initial look at the data and

An overview of your `eeg_df` DataFrame, we can use the `.info()` method. This provides a concise summary of the DataFrame, including the number of entries, column names, non-null counts, and data types.



The screenshot shows a Jupyter Notebook interface with a file explorer on the left and a code editor on the right. The file explorer shows files: `Confusion-EEG.ipynb`, `EEG_data.csv`, `README.md`, and `demographic_info.csv`. The code editor shows the following code and output:

```
SubjectID  VideoID  Attention  Mediation  Raw  Delta  Theta \
0         0.0      0.0       56.0      43.0  278.0  301963.0  90612.0 \
1         0.0      0.0       40.0      35.0   -50.0   73787.0  28083.0 \
2         0.0      0.0       47.0      48.0  101.0   758353.0  383745.0 \
3         0.0      0.0       47.0      57.0   -5.0   2012240.0  129350.0 \
4         0.0      0.0       44.0      53.0   -8.0   1005145.0  354320.0 \

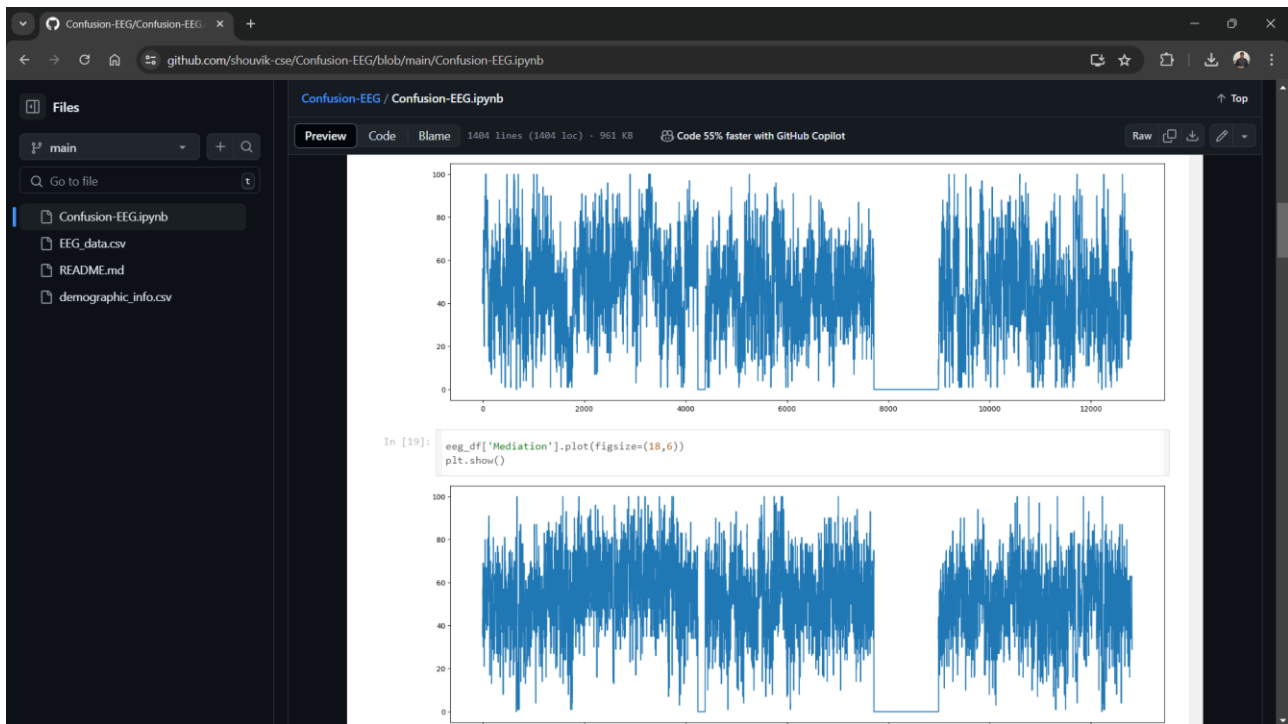
Alpha1  Alpha2  Beta1  Beta2  Gamma1  Gamma2  predefinedlabel \
0  33735.0  23991.0  27946.0  45097.0  33228.0  8293.0          0.0 \
1  1439.0   2240.0   2746.0   3687.0   5293.0   2740.0          0.0 \
2  201999.0  62107.0  36293.0  130536.0  57243.0  25354.0         0.0 \
3   61236.0  17084.0  11488.0   62462.0  49960.0  33932.0         0.0 \
4   37102.0  88881.0  45307.0  99603.0  44790.0  29749.0         0.0 \

user-definedlabel
0         0.0
1         0.0
2         0.0
3         0.0
4         0.0

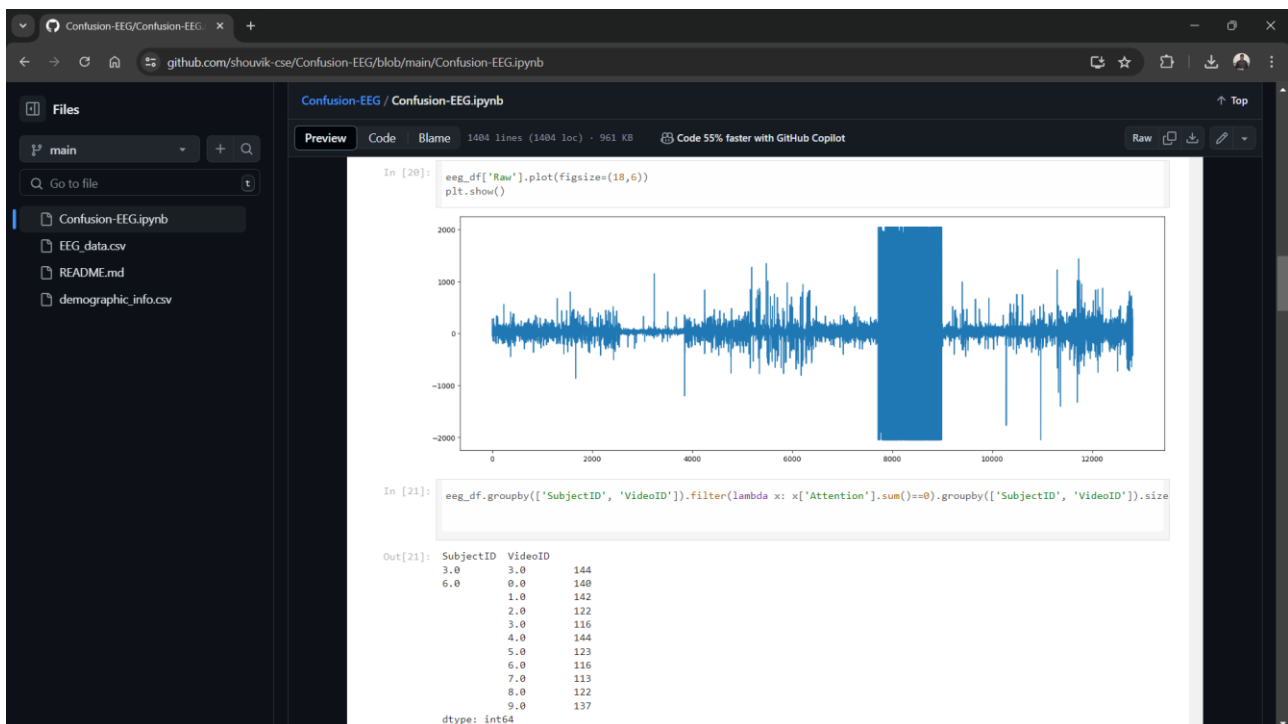
In [17]: eeg_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12811 entries, 0 to 12810
Data columns (total 15 columns):
#   Column              Non-Null Count  Dtype  
---  -
0   SubjectID            12811 non-null  float64
1   VideoID              12811 non-null  float64
2   Attention             12811 non-null  float64
3   Mediation             12811 non-null  float64
4   Raw                  12811 non-null  float64
5   Delta                12811 non-null  float64
6   Theta                12811 non-null  float64
7   Alpha1               12811 non-null  float64
8   Alpha2               12811 non-null  float64
9   Beta1                12811 non-null  float64
10  Beta2                12811 non-null  float64
11  Gamma1               12811 non-null  float64
12  Gamma2               12811 non-null  float64
13  predefinedlabel       12811 non-null  float64
```

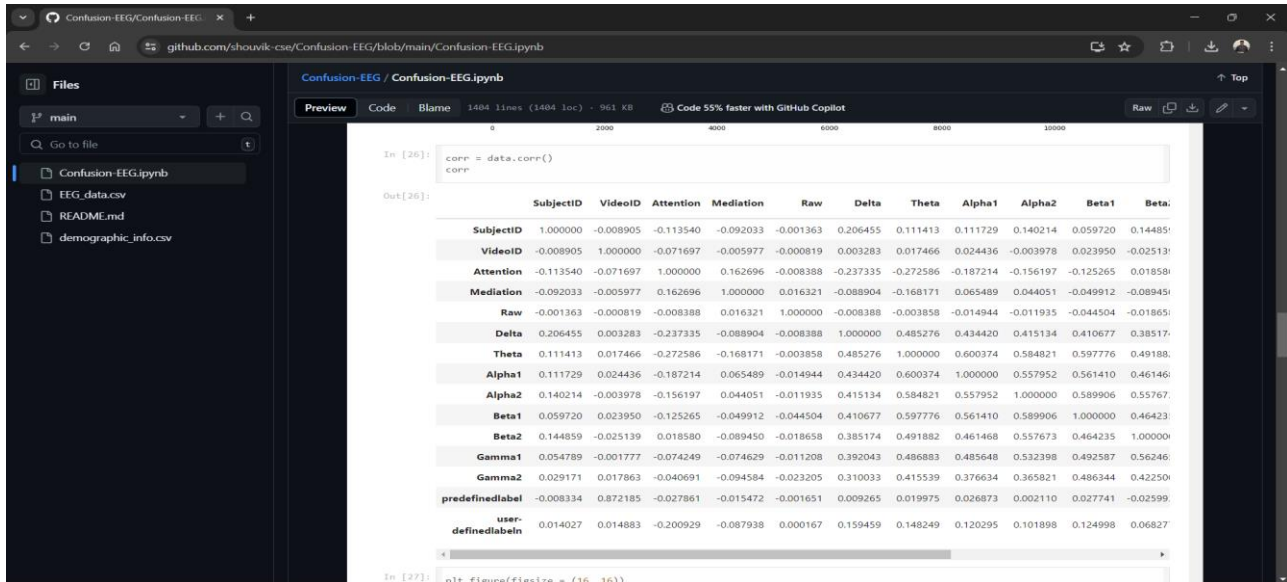
Plotting the 'Attention' column and the 'Mediation' column from `eeg_df` Data Frame



Plotting the 'Raw' column from `eeg_df` Data Frame



To calculate the correlation matrix for DataFrame, we use the `.corr()` method. This method computes pairwise correlation of columns, excluding NA/null values.



The screenshot shows a Jupyter Notebook interface with a file explorer on the left containing 'Confusion-EEG.ipynb', 'EEG_data.csv', 'README.md', and 'demographic_info.csv'. The main area displays the following code and output:

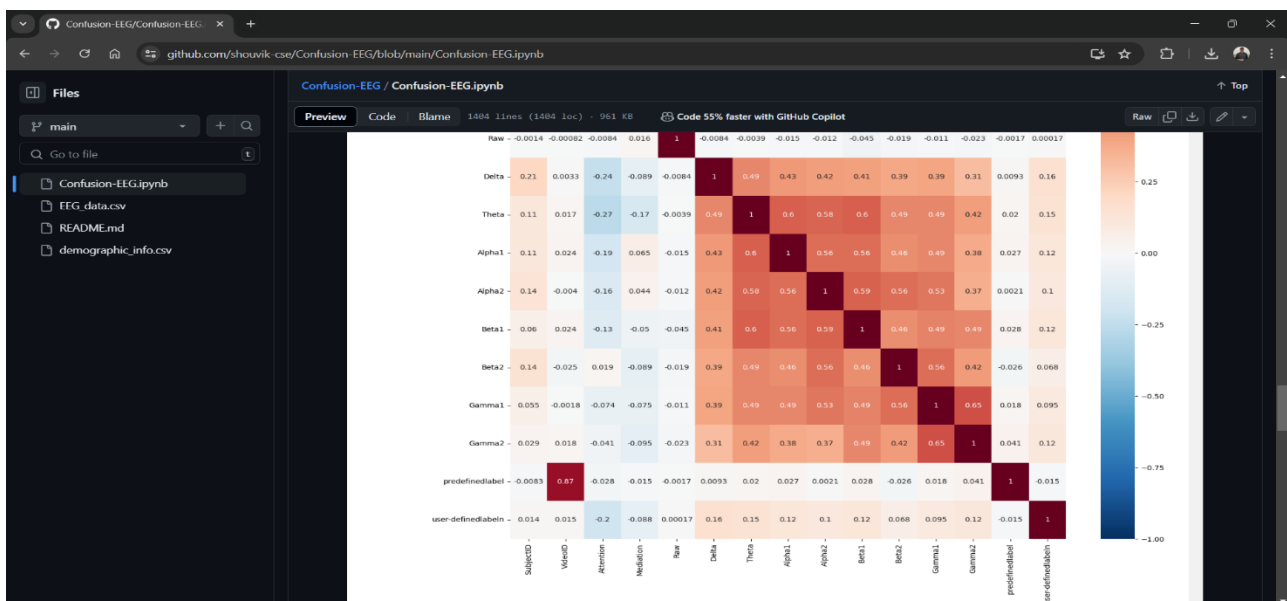
```
In [26]: corr = data.corr()
         corr
```

```
Out[26]:
```

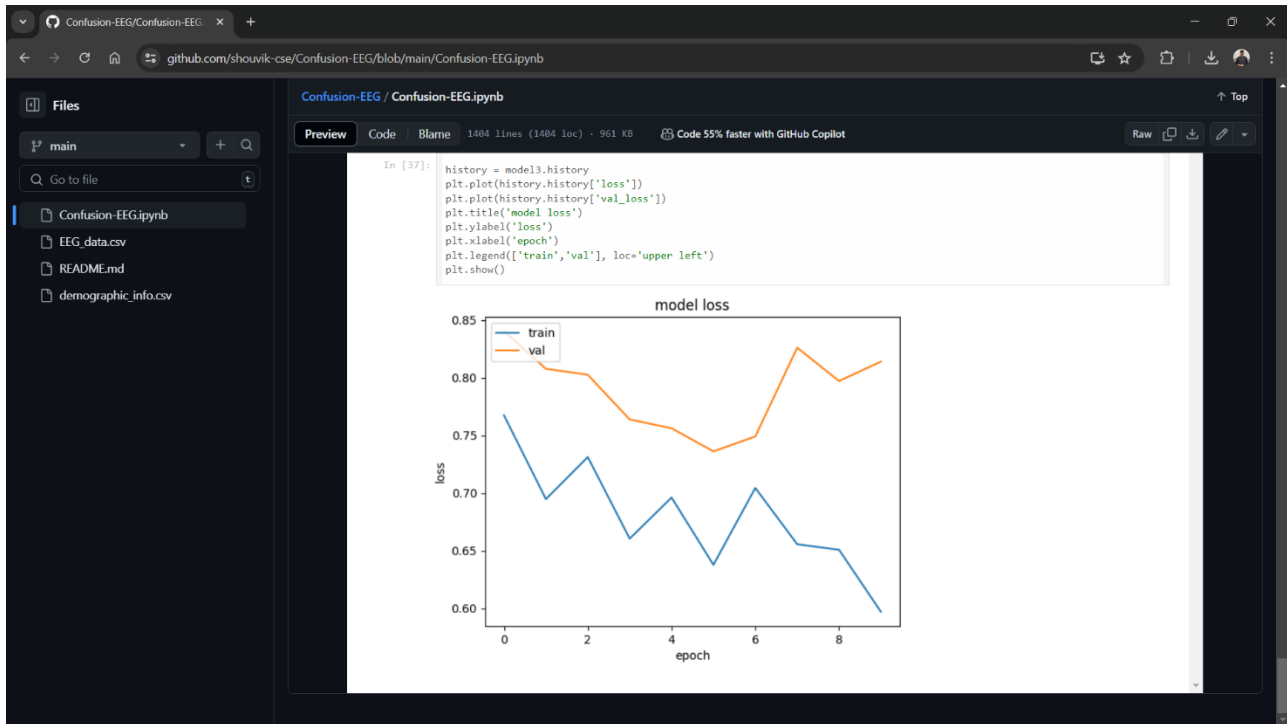
	SubjectID	VideoID	Attention	Mediation	Raw	Delta	Theta	Alpha1	Alpha2	Beta1	Beta2
SubjectID	1.000000	-0.008905	-0.113540	-0.092033	-0.001363	0.206455	0.111413	0.111729	0.140214	0.059720	0.144851
VideoID	-0.008905	1.000000	-0.071697	-0.005977	-0.000819	0.003283	0.017466	0.024436	-0.003978	0.023950	-0.025131
Attention	-0.113540	-0.071697	1.000000	0.162696	-0.008388	-0.237335	-0.272586	-0.187214	-0.156197	-0.125265	0.018581
Mediation	-0.092033	-0.005977	0.162696	1.000000	0.016321	-0.088904	-0.168171	0.065489	0.044051	-0.049912	-0.089451
Raw	-0.001363	-0.000819	-0.008388	0.016321	1.000000	-0.008388	-0.003858	-0.014944	-0.011935	-0.044504	-0.018651
Delta	0.206455	0.003283	-0.237335	-0.088904	-0.008388	1.000000	0.485276	0.434420	0.415134	0.410677	0.385171
Theta	0.111413	0.017466	-0.272586	-0.168171	-0.003858	0.485276	1.000000	0.600374	0.584821	0.597776	0.491881
Alpha1	0.111729	0.024436	-0.187214	0.065489	-0.014944	0.434420	0.600374	1.000000	0.557952	0.561410	0.461461
Alpha2	0.140214	-0.003978	-0.156197	0.044051	-0.011935	0.415134	0.584821	0.557952	1.000000	0.589906	0.557671
Beta1	0.059720	0.023950	-0.125265	-0.049912	-0.044504	0.410677	0.597776	0.561410	0.589906	1.000000	0.464231
Beta2	0.144851	-0.025131	0.018581	-0.089451	-0.018651	0.385171	0.491882	0.461461	0.557673	0.464235	1.000000
Gamma1	0.054789	-0.001777	-0.074249	-0.074629	-0.011208	0.392043	0.486883	0.485648	0.532398	0.492587	0.562461
Gamma2	0.029171	0.017863	-0.040691	-0.094584	-0.023205	0.310033	0.415539	0.376634	0.365821	0.486344	0.422501
predefinedlabel	-0.008334	0.872185	-0.027861	-0.015472	-0.001651	0.009265	0.019975	0.026873	0.002110	0.027741	-0.025991
user-definedlabel	0.014027	0.014883	-0.200929	-0.087938	0.000167	0.159459	0.148249	0.120295	0.101898	0.124998	0.068271

```
In [27]: plt.figure(figsize = (35, 16))
```

To generate a heatmap of the correlation matrix for `eeg_df` DataFrame, we will first need to calculate the correlation matrix, then use Seaborn's heatmap function to visualize it.



To plot the training and validation loss from a Keras model history (`model3.history`), we can use the following code. This assumes that `model3` has been trained and its history object (`model3.history`) contains the loss and validation loss values across epochs.



Chapter 4

Conclusion

Ultimately, this research proposal on "Confusion Level Detection Using EEG Signal Analysis" offers a great chance to further our understanding of cognitive states, notably confusion, through the creative use of EEG signal analysis. The research seeks to produce an objective measurement tool capable of identifying and tracking confusion levels in real-world events using a systematic method that includes data collecting, preprocessing, model development, and real-time implementation. In order to ensure participant welfare, privacy, and informed consent, ethical issues are crucial. The possible applications of this research span a wide range of industries, including human-computer interaction, education, and healthcare, and promise individualized interventions and improved decision-making. Continuous development and iterative improvement demonstrate our dedication to building a dependable and flexible solution that adapts to user feedback and actual facts. This study is a call to action that encourages cooperation and commitment to ethical and acceptable research techniques with the ultimate goal of advancing knowledge about confusion and its broader societal ramifications.

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- [5] [Claire Receli M. Reñosa](#); [Argel A. Bandala](#); [Ryan Rhay P. Vicerra](#)- Classification of Confusion Level Using EEG Data and Artificial Neural Networks, 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), 29 November 2019 - 01 December 2019.
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