NeuraLie: An EEG-based Tri-Modal Approach for Deception Detection

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Certificate of Approval

It is certified that the work presented in this report was performed by **Muhammad Maaz Tariq, Mohmmad Arslan, Shaheer Alam, and Muhammad Afzal** under the supervision of **Dr. Zahid Halim, Engr. Ahsan Shah, Engr. Talha Laique.** The work is adequate and lies within the scope of the BS degree in Computer Science/Computer Engineering at Ghulam Ishaq Khan Institute of Engineering Sciences and Technology.

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ABSTRACT

NeuraLie is an AI-based lie detection solution that utilizes the subject's brain waves (EEG signals) along with other elusive physical cues, namely facial expressions and eye-blinking patterns, to detect deception. This particular approach not only aims to address the limitations and inaccuracies of the conventional polygraph but has also aimed to revolutionize the efficacy of lie detection systems in general. The conventional polygraph test uses only physiological responses making them less effective and unreliable, as has been proved over the years. NeuraLie will make use of an EEG headset and a camera, which will send inputs to the NeuraLie web application running on the computer they are connected to. The procedure will be the same as in current lie detection techniques, involving an examiner/interviewer and a subject being monitored by the hardware. The interviewers can get themselves registered, allowing multiple interviewers to make use of the same machine and have their own logs stored locally for future reference. The data collected from the two hardware interfaces, EEG headset, and camera, are sent for processing on the backend, after which they are given as input to the three Deep Learning models that NeuraLie utilizes. The results are ensembled to reach a conclusive result, which is a binary classification between truth and lies.

This document explains the design, development, and comprehensive description of NeuraLie, which comprises three Deep Learning models and a web application for interacting with the system.

ACKNOWLEDGEMENTS

We would like to express our sincere gratitude to all the individuals who have contributed to the successful completion of this final year project.

First and foremost, we would like to thank our project supervisors, Dr. Zahid Halim, Engr. Ahsan Shah, and Engr. Talha Laique for his invaluable guidance, support, and encouragement throughout the project. His vast knowledge, experience, and expertise have been instrumental in shaping the direction and scope of the project. Thanks to his guidance, we were able to take our project to a competitive scale and win the Jury's Choice Award at the Microsoft Imagine Cup 2023.

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I would like to acknowledge the support and assistance provided by Dr. Khurram Khan Jadoon as well, who has generously shared his time and knowledge with us during the implementation stages.

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Chapter 1: Introduction

A Polygraph refers to a device and/or procedure that can determine whether a person is lying or not. It does this by taking various physiological readings such as blood pressure, heart rate, respiration, and skin conductivity. Taking inspiration from the existing Polygraph method and analysing its shortcomings, our group, as part of our Final Year Project, collectively made the effort to revolutionize the Lie Detection industry. Our objective was to create a more accurate and modern alternative to the conventional polygraph, which we name "NeuraLie", to achieve this objective we intend to reinvent the polygraph by infusing it with modern Artificial Intelligence and Machine Learning technology. This Introductory chapter of our Final Year Project Report provides an overview of our project's objectives and motivations for our Final Year Project which from here on will be called "FYP". The aim of this FYP report is to present a detailed description of the building process of "NeuraLie" and present the results we could produce.

Motivation

The primary motivations for NeuraLie were that existing state of the art conventional lie detection systems and techniques are either too expensive and bulky to set up in the case of functional magnetic resonance imaging (fMRI) or can be passed by a trained subject in the case of the Polygraph test. Conventional Lie detection systems are also not admissible in court with the creation of NeuraLie we intend to make lie-detection accurate enough to be admissible in court with the goal of serving justice.

Functional Magnetic Resonance Imaging[2]

The method of using strong magnets to map brain activity by measuring the brain's oxygen consumption has great potential for detecting lies. However, this technology still has significant limitations, including invasiveness, inaccuracy, and the bulky and expensive nature of fMRI machines, which can cost over $300,000. Additionally, fMRI machines are sensitive to even minor head movements, which can be used as a countermeasure to make the collected data unusable.

Polygraph

The polygraph is a device used to measure physiological indicators, such as blood pressure, pulse, respiration, and skin conductivity, while a person is questioned. It is based on the belief that deceptive answers produce distinct physiological responses that can be distinguished from those associated with truthful responses. However, there are no specific physiological reactions that are exclusively associated with lying, making it challenging to identify factors that indicate deception.

According to Wired magazine, an estimated 2.5 million polygraph tests are administered annually in the United States, with most given to paramedics, police officers, firefighters, and state troopers. The average cost of a test is more than $700, contributing to a $2 billion industry.

Although the use of polygraphs remains controversial, they are widely used in post-conviction supervision. Scientific and government bodies have evaluated polygraphs and concluded that they are not a reliable means of assessing truthfulness, as they can be defeated by countermeasures and are prone to inaccuracies. Despite advocates' claims of 80-90% accuracy, the National Research Council has found no evidence to support this. Many innocent subjects experience heightened physiological reactions to crime-relevant questions, and the polygraph measures arousal, which can be influenced by various factors such as anxiety, PTSD, nervousness, fear, confusion, hypoglycemia, psychosis, and depression. Two major types of countermeasures exist: "general state" and "specific point," which aim to alter the physiological or psychological state of the subject during specific examination periods to either increase or decrease responses.

Our Solution/NeuraLie

The solution that "NeuraLie" provides is a lightweight, cheaper, and relatively harder to beat lie detection system. It identifies a lying test subject by recording their EEG signals, eye blinking patterns and facial expressions. This data is then used to generate predictions as to whether the subject is lying or not using AI and ML techniques.

Now, this begs the question, what makes the use of EEGs for deception detection more desirable or favorable when compared with polygraphy? The straightforward answer to that would be that EEGs record brain activity in certain areas of the brain when certain items or events are recognized before we are even conscious that we recognize them, so they cannot be suppressed and/or inhibited on demand. This makes it almost impossible to cheat them, unlike polygraphs, which have proved to have loopholes where a trained subject can use some mental cues or trigger physiological reactions that can alter test results in the subject's favor.

To augment our system and make it more reliable facial expressions and eye blinking patterns are used alongside EEG signals to generate predictions.

Objectives

The objective behind "NeuraLie" is to utilize the potential of Artificial Intelligence to predict and identify lies amongst truths no matter what form of setting much more accurately than a conventional polygraph does. The goal is to automate and make the interrogation and justice process more reliable and automated.

It is aimed to identify and classify a lying test subject by taking their EEG signals, eye blinking patterns, and facial expressions as input. The product shall take inputs on all three different channels and then send these inputs to the respectively trained models on the back end. The Artificial Intelligence based models on the back end take these inputs as test data and perform binary classification predicting whether the user is lying. In the end, there is a separate module for the pooling of the outputs from the three models to predict the final output, that is if the subject is lying or not.

Project Scope

The prime intention of this project is to revolutionize the lie detection process with the latest technological marvels the world is experiencing. It is aimed to identify and classify a lying test subject by taking their EEG signals, eye blinking patterns, and facial expressions as input. It is an attempt to make the lie-detection process more accurate enough to be admissible in court with the goal of serving justice and eliminating injustice in modern-day life.

Product Functioning

An interviewer logs in to the system by entering his credentials. After logging in the user has two options to conduct an interview or to view logs of previous interviews, both options have their respective buttons on the home page. To view logs the user clicks the view logs button and is taken to the logs page where logs of previous interviews are displayed, that is the time the interviews were taken and their results. To conduct an interview the user clicks on the conduct interview button on the home page, and he is redirected to the interview page where the user records videos of the interviewee with an attached webcam and an using an EEG headset records EEG signal of the interviewee. This data is then passed to their respective models which then produce predictions that are combined into one final prediction and displayed to the interviewer.

User Characteristics

The following section describes and identifies the single unique user for our project, "NeuraLie":

User who administers the test

This is the one and only kind of user for the system and is the individual who has an account made on the web interface. The user signs in with his account credentials and runs the pretest interview for the initial interview readings of the interviewee. The user then asks the actual questions, and the input from the user is fed to the models on the backend, which outputs the result. The same user can also view the log history of the previous results of the interviews that have been taken by the same user account.

System Overview

Process View

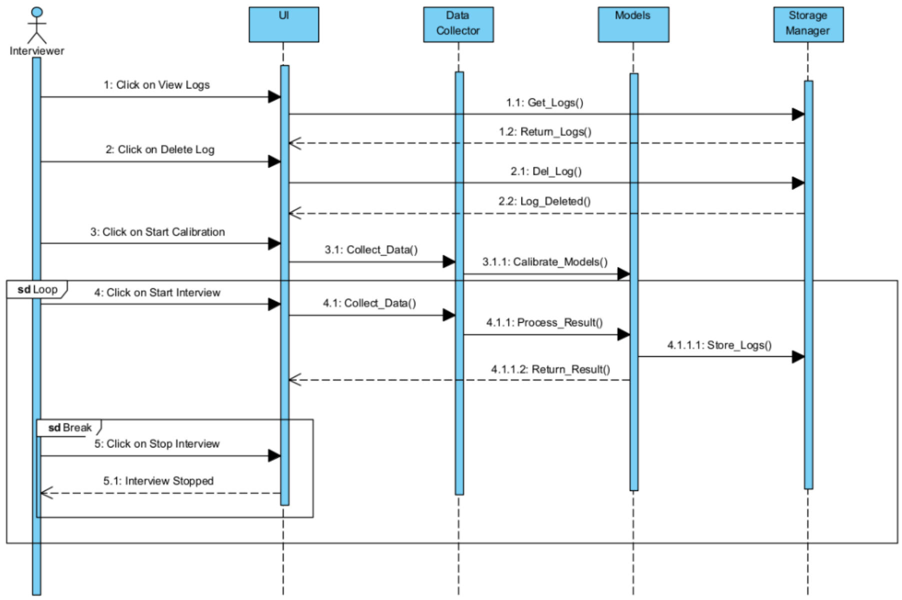

Figure 1 Process View

Physical View

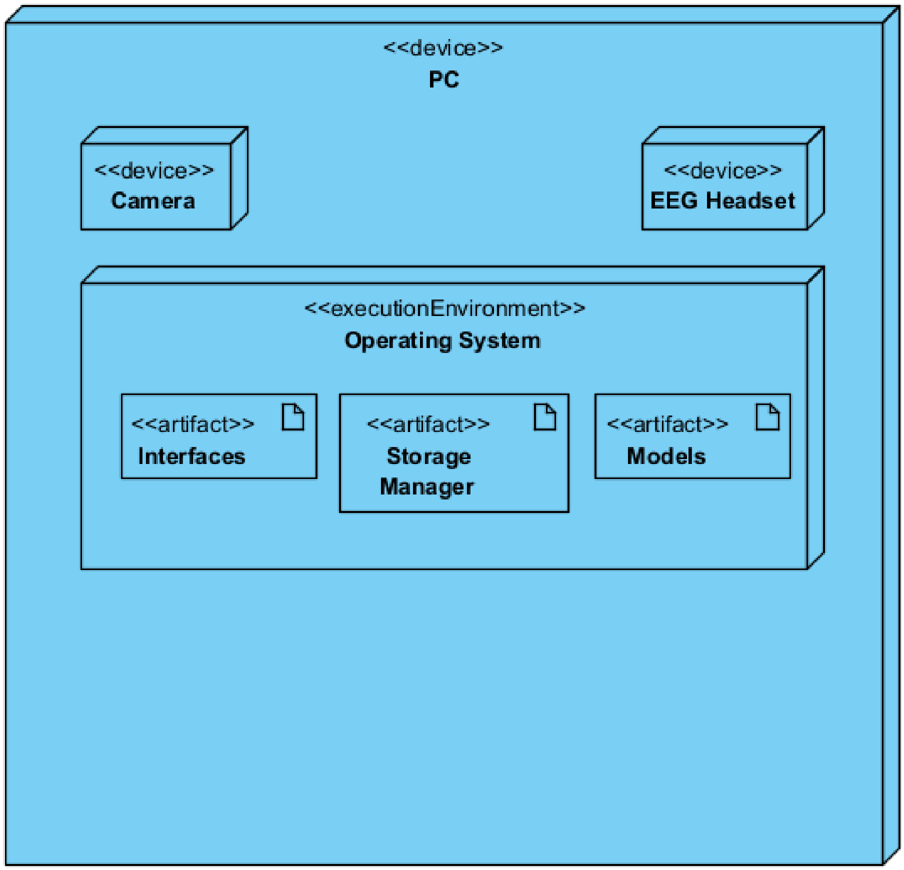

Figure 2 Physical View

Chapter 2: Literature Survey

There has been substantial research done in deception detection, including unimodal and multi-modal approaches in a variety of combinations of modalities. This literature review aims to discuss two research papers that have specialized in EEG-based deception using various classification algorithms and feature extraction methods, the accuracies of which are then compared. It also aims to discuss a research paper from each of the other two modalities that are comprised in NeuraLie: facial expressions and eye-blinking patterns. With all that in mind, this literature review will establish the reasons for using the three modalities that NeuraLie uses for deception detection and why exactly NeuraLie employs a tri-modal approach.

A Survey for Lie Detection Methodology Using EEG Signal Processing[3]

This research paper analyzes multiple techniques and algorithms that have been used to perform deception detection using EEG signal processing. Each of these techniques employs various kinds of classification techniques, feature extraction methods, and EEG signals datasets. Many categorization approaches were employed in EEG lie.
detection systems. Multi-class support vector machines (SVM) were used majorly in this research.

There are two categories of datasets used in published research: public datasets and private datasets. Some studies have used the public database, such as the Dryad dataset available on the dryad database. This dataset is used for the model's training and validation.

Truth Identification from EEG Signal by using Convolution neural network: Lie Detection[4]

The objective of this paper is to automatically identify truthfulness from EEG signals using a deep learning technique that employs a convolutional neural network (CNN). The model is designed to take 14-channel EEG signals as input and classify them as truth or lie statements. The proposed method achieves an accuracy of up to 84.44%, making it efficient, non-invasive, and suitable for real-time applications. Furthermore, it is robust and has low time complexity.

The Dryad dataset is used to perform the training and validation of the proposed model. There were thirty subjects who were divided randomly into guilty and innocent groups. Six jewels pictures served as stimuli during detection. Three types of stimuli were defined in the experiment (irrelevant, probe, target) The EEG signals on 14 electrodes were recorded. A novel spatial denoising algorithm (SDA) was proposed to reconstruct the P300 with a high SNR based on the independent component analysis. Here is a representation of the Dryad dataset used for the experiment:

Table 1 The Dryad Dataset

Category	Sub-Category	Total Samples
Honest	Honest irrelevant	50
	Honest probe	50
	Honest target	50
Lying	Lying irrelevant	50
	Lying probe	50
	Lying target	50
Total		300

The dataset consists of 300 samples, with 150 in each of two categories. The dataset is further divided into three sub-categories, with 50 samples in each category. The Honest Irrelevant set, Honest Probe set, and Honest Target set each contain 50 samples, while the Lying Irrelevant set, Lying Probe set, and Lying Target set also contain 50 samples each. In addition, a new dataset was created specifically for the experimental analysis of EEG lie detection. This dataset includes 50 samples, each with 14 channel EEG signals obtained using a 14 Channel Mobile Brainwear headset. The dataset was prepared with the help of the university, and the subjects were university students who answered five questions each. Ground truth was determined at the end by these subjects.

Table 2 EEG Lie Detection Dataset

Category	Total Samples
Truth	25
Lie	25
Total	50

The dataset comprises 50 samples categorized into two groups with 25 samples each. These samples are further split into a training set and a testing set with a ratio of 4:1. Specifically, the training dataset consists of 40 samples (20 samples per category), while the testing dataset comprises 10 samples (5 samples per category).

DeepLie: Detect Lies with Facial Expression (Computer Vision)[5]

This research introduces a novel computer vision-based technique for detecting lies in video streams, building on previous work. The approach employs deep learning to recognize universal micro-expressions displayed by humans when they lie in front of a camera.

To accomplish the learning task, two primary datasets were used. The first dataset includes faces with corresponding expressions, while the second dataset comprises video clips of individuals telling the truth or lying. The researchers employed FER-2013, which is available on Kaggle, to train the expression recognizer. The training dataset comprises 28,709 examples, and the test set contains 3,589 examples, with each image pre-cropped to focus only on the human face and labeled with numbers 0-6. For the video clip data, the researchers utilized a labeled set of 60 truths and 61 lies, which was also used in a prior paper titled "Deception detection in videos," presented at AAAI 2018, as cited below. Each video has an average length of approximately 2 minutes and is in mp4 format with a frame rate of 30 frames per second. The videos only show the person making a statement, and the appearances of judges or other people are rare and insignificant for training purposes.
The research presents an all-in-one approach that incorporates various elements to identify deceitful statements in videos based on facial expressions extracted from each frame of the video. The proposed technique employs a 2-layer GRU network model that can detect recurring patterns of facial expressions and small facial muscle movements to detect lies. To address the one-shot learning issue and avoid overfitting data based on unique facial characteristics, the DeepLie algorithm uses a Siamese network architecture with triplet loss based on a dataset of 61 truths and 60 lies in court videos. The algorithm creates an embedding space that effectively differentiates between truthful and deceptive videos.

Deceptive Information Detection through Computer Vision Analysis of Facial Micro-Expressions from Depth Video Stream[6]

Before discussing the existing literature on the usage of eye-blinking patterns for lie detection, it is essential to discuss the credibility of this modality and why it is an effective technique for detecting deception. The following study analyzes the correlation between eye-blinking frequency and cognitive demand:

Effect of Awareness on an Indicator of Cognitive Load[7]

The experiment confirms that cognitive load has an impact on blinking, with task difficulty leading to increased cognitive load and a reduction in blinking, which helps to minimize any interference that blinking may cause in task-directed cognitive processes.

This research project utilized multiple computer vision techniques for lie detection, with the eye-blinking pattern being particularly relevant. The authors based their approach on the established hypothesis from eye blink literature that liars experience more cognitive demand than truth tellers, resulting in a significant decrease in eye blinks during lying, followed by an increase in eye blinks when the cognitive demand subsides. Their dataset included nine recorded interviews.

There are also isolated projects that focus solely on blink detection and counting. In one such project, the eye-aspect ratio is utilized to determine if a person is blinking or not in each video frame. The implementation involves using Python, OpenCV, and dlib code to perform facial landmark detection and detect blinks in video streams. The approach is tested using webcam streams and video files to detect blinks.

Discussion

This literature review has shown the various attempts and research that have independently been conducted on each of the modalities that NeuraLie will be incorporating into its system design.

There are significant reasons why NeuraLie has been made a multimodal approach instead of a unimodal one. Recent research on deception detection has brought together scientists from fields as diverse as computational linguistics, speech processing, computer vision, psychology, and physiology, which makes this problem particularly appealing for multimodal processing.

In general, a multimodal approach where features from different streams are integrated is found to lead to improved performance as compared to the use of single modalities.

The most prominent ways that deception can be observed is through intercepting and analyzing thoughts, where a clear distinction is seen in the thinking patterns of a person telling the truth and a person trying to deceive. Hence, we have incorporated the use of EEG signals which, as discussed earlier, do not pose the disadvantages of being easy to cheat as the case is with the conventional polygraph still in use today. Second, deception is shown first on the face, from which we derive two essential modalities, facial expressions, and eye blinking patterns, both proven to be very effective in fishing deception. Another modality could have been Voice Stress Analysis (VSA). Voice-stress analysis can identify stress levels in speech, but high levels of stress do not necessarily correlate with deception. An innocent person may be stressed out before the exam since interrogation is quite a stressful situation to be in. Hence, this modality was not favored over the chosen ones.

Chapter 3: Design (Systems Requirements/Specifications)

Overall Description

The prime intention of this project is to revolutionize the lie detection process with the latest technological marvels the world is experiencing. It is aimed to identify and classify a lying test subject by taking their EEG signals, eye blinking patterns, and facial expressions as input. The product shall take inputs on all three different channels and then send these inputs to the respectively trained models on the back end. The Artificial Intelligence based models on the back end take these inputs as test data and perform binary classification predicting whether or not the user is lying. In the end, there is a separate module for the pooling of the outputs from the three models to predict the final output if it is a truth or a lie.

Product Perspective

The idea behind "NeuraLie" is to utilize the potential of Artificial Intelligence in order to predict and identify lies amongst truths no matter what form of setting much more accurately than a conventional polygraph does. The goal is to automate and make the interrogation and justice process more reliable and automated.

Product Functions

The key features of "NeuraLie" are as follows:

1. A web-based user interface for the user to interact with the models and obtain a conclusive result
2. Collection of inputs using hardware interfaces
3. Calibration of models to the inputs from the pretest interview

4. Testing of new inputs on pre-trained models on the backend
5. Pooling of outputs from models to give one conclusive output
6. Viewing of logs to be referred for any past references

User Characteristics

The following section describes and identifies the single unique user for our project, "NeuraLie":

User who administers the test

This is the one and only kind of user for the system and is the individual who has an account made on the web interface. The user signs in with his account credentials and runs the pretest interview for the initial interview readings of the interviewee. The user then asks the actual questions, and the input from the user is fed to the models on the backend, which output the result. The same user can also view the log history of the previous results of the interviews that have been taken by the same user account.

User/System Requirements

External Interface Requirements

User interface

This section shows the wireframes that were created during the initial stages of the project. The screenshots of the final UI can be found in the Results section. The user interfaces for the NeuraLie web application are as follows. There are 5 main screens, 3 of which are for each of the interviewing functionalities that the web application provides. Namely, calibration, interviewing and viewing logs. The user is first shown a login screen, after which he/she is taken to the dashboard.

Figure 3 Home Page

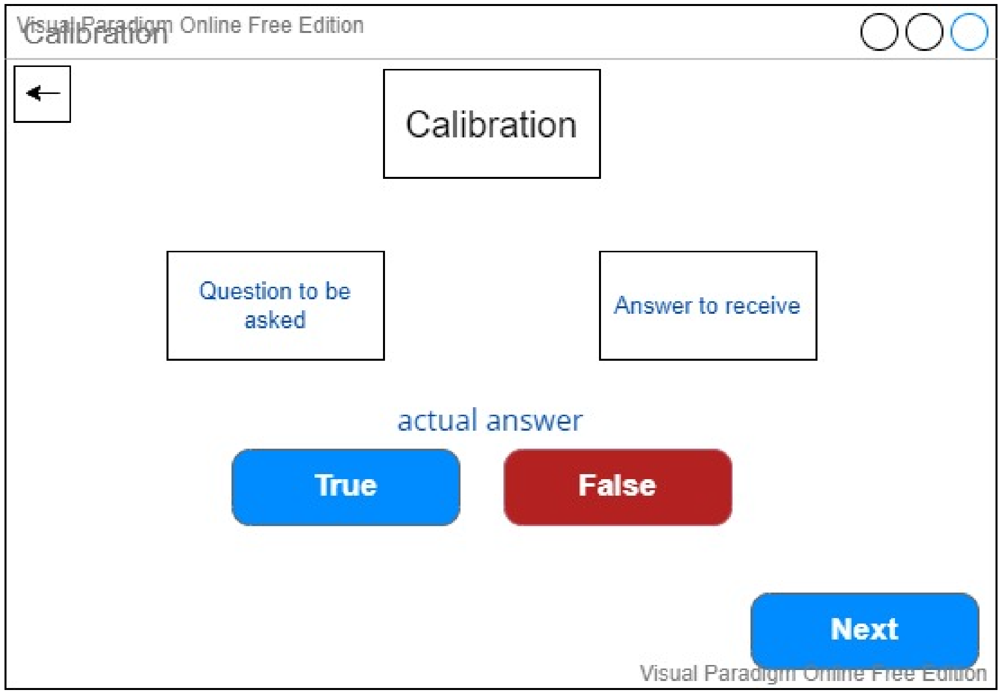

Figure 4 Calibration Page \

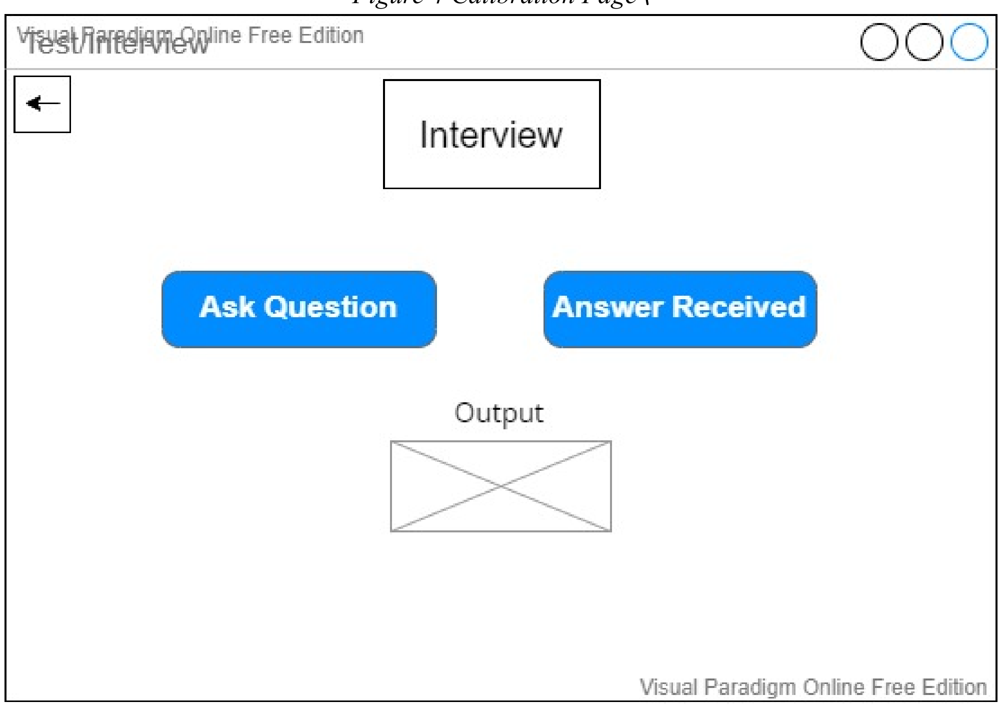

Figure 5 Interview Page

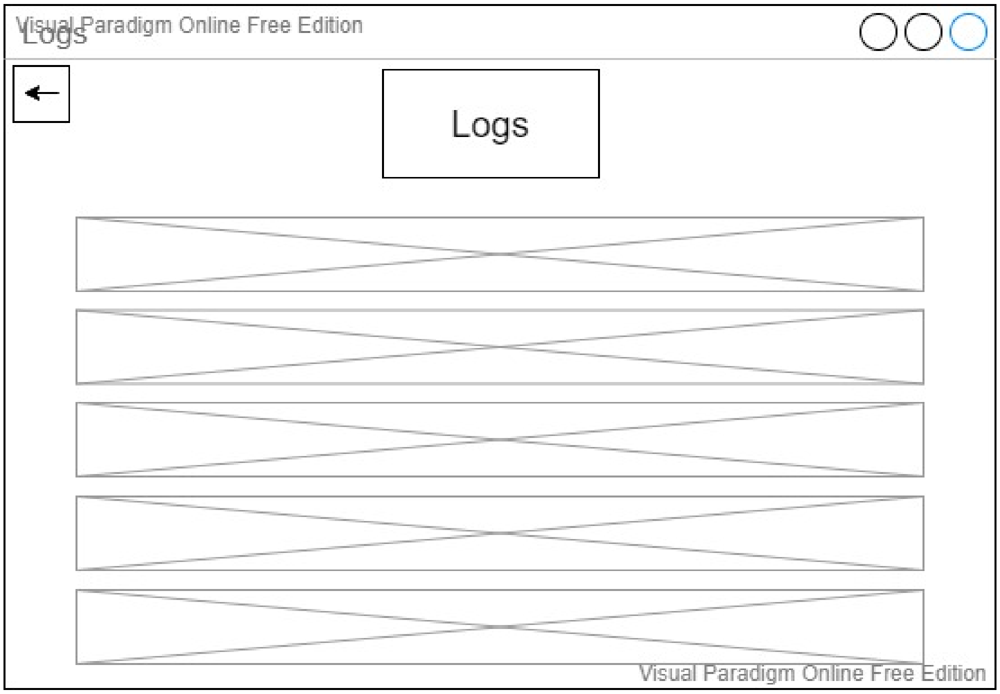

Figure 6 Logs Page

Hardware interface

- The Nexstem EEG headset has 16 active electrodes strategically placed to provide optimum coverage of the brain and capture all the signals. It connects via Bluetooth 5.0, Wi-fi, and also a micro-USB cable. For the headset's interface with the brain, 15-pin dry EEG electrodes are used.
- Camera: A standard HD webcam used for real-time video input of the subject that has to be fed to the facial expressions and eye-blink pattern models.

Software Interface

- Web application built on the Django framework.
- For the storage of logs, local storage will be used since separate databases are not a necessity.
- The headset is also preconfigured to connect to the SDK hosted on Microsoft Azure. This helps create customized BCI applications and devices.
- The 3 ML models will be mounted to the web application, which will send input received from the hardware devices to the models as input and receive output from the models, which will then be displayed for the user.
- OpenCV will be used to process real-time video feed received from the webcam, which will be used by the facial expressions model and the eye-blink pattern model.

Communication Interface

- All communications from and to the web application are made via HTTPS.
- The EEG headset and camera both connect to the computer via micro-USB cables.
- BLE: Bluetooth Low Energy v5.0 support coming
- EEG Signals:
- Resolution: 24-bit ADC
- Sampling Rate - 1000 Samples/second
- Bandwidth: 0.1 Hz to 50Hz

Functional Requirements

User Registration/Login

Description

This feature enables the user to get themselves registered with the system. Also, this feature will ensure the authenticity of the user.

Stimulus/Response Sequences

Normal Path: User Registers with Web App successfully
Preconditions • User must open the provided web app
Interactions • The user clicks the "Register" button
Post conditions • "Registration Successful" message is displayed • Afterwards, the user is taken to Home Screen of the web app

Categorization

- Criticality: High
- Probability of Defects: Low
- Risk: Medium

Exceptional Path: An error message is displayed

Preconditions

- User enters invalid credentials
- User enters invalid verification code

Interactions

- An exception is thrown in the system.

Postconditions

- Error message is displayed

Categorization

- Criticality: High
- Probability of Defects: Low
- Risk: High

Functional Requirement

REQ-1 The web app shall enable users to get themselves registered with the system.

REQ-2 The web app shall take the user's credentials, including name, email address, and password as input.

REQ-3 The web app shall authenticate the user's input data by matching verification code with the system's database.

REQ-4 Only, in case of successful authentication, the web app shall take the user to the home screen.

REQ-5 In case, the user signs out of the web the app, user shall only be able to use web app's functionality once user has signed back into the web app after providing email address & password, as input to the web app.

Interviewee Information

Description

This feature enables the user to enter the information of the interviewee.

Stimulus/Response Sequences

Normal Path: User successfully enters information into the web app
Preconditions • User must log into the provided web app
Interactions • The user clicks "New Interviewee" button • The user enters interviewee information • The user clicks "Save" button
Post conditions • "Saved Successfully" message is displayed • Afterwards, the user is taken to calibration screen of the web app
Categorization • Criticality: High • Probability of Defects: Low • Risk: Medium

Exceptional Path: An error message is displayed
Preconditions • User enters invalid characters
Interactions • An exception is thrown in the system.
Postconditions • Error message is displayed
Categorization • Criticality: High • Probability of Defects: Low • Risk: High

Functional Requirement

REQ-6 The web app shall enable users to enter and save interviewee information into the system.

REQ-7 The web app shall take the interviewee's credentials, including name, gender, and age, as input.

REQ-8 The web app shall authenticate the user's input data by matching valid characters with the system's database.

REQ-9 Only, in case of successful authentication, the web app shall take the user to the calibration screen.

REQ-10 In case the user signs out of the web app, the user shall only be able to use the web app's functionality once the user has signed back into the web app after providing the email address & password as input to the web app.

Calibration Session

Description

This feature enables the user to conduct a calibration session with the interviewee.

Stimulus/Response Sequences

Normal Path: User successfully calibrates the system
Preconditions • User must enter interviewee information

Interactions • The user clicks the "Calibrate" button • The system validates input from all modalities and calculate average blinks • The user clicks "Continue" button
Post conditions • "Calibration Successful" message is displayed • Afterwards, the user is taken to interview screen of the web app
Categorization • Criticality: High • Probability of Defects: Low • Risk: Medium

Exceptional Path: An error message is displayed
Preconditions • System unable to validate input from modalities

Interactions • An exception is thrown in the system.
Postconditions • Error message is displayed
Categorization • Criticality: High • Probability of Defects: Low • Risk: High

Functional Requirement

REQ-11 The web app shall enable users to start a calibration session.

REQ-12 The web app shall validate inputs from hardware.

REQ-13 The web app shall calculate the average blinks of the interviewee.

REQ-14 Only, in case of successful calibration, the web app shall take the user to the interview screen.

REQ-15 In case the user signs out of the web app, the user shall only be able to use the web app's functionality once the user has signed back into the web app after providing an email address & password as input to the web app.

Interview

Description

This feature enables the user to conduct the actual interview.

Stimulus/Response Sequences

Normal Path: User successfully conducts the interview
Preconditions • User must calibrate the system
Interactions • The user clicks "Start Interview" button • The user clicks "End Interview" button

Post conditions • "Interview Successful" message is displayed • Afterwards, the user is taken to the home screen of the web app
Categorization • Criticality: High • Probability of Defects: Low • Risk: Medium

Exceptional Path: An error message is displayed
Preconditions • Unable to receive input from hardware
Interactions • An exception is thrown in the system
Post conditions • Error message is displayed

Categorization

- Criticality: High
- Probability of Defects: Low
- Risk: High

Functional Requirement

REQ-16 The web app shall enable users to start and end the interview.

REQ-17 The web app shall read input values from the hardware during the session.

REQ-18 The web app shall process the input values to display an output.

REQ-19 Only, in case of successful authentication, the web app shall take the user to the home screen.

REQ-20 In case the user signs out of the web app, the user shall only be able to use web app's functionality once user has signed back into the web app after providing email address & password, as input to the web app.

View Logs

Description

This feature enables the user to view interview logs.

Stimulus/Response Sequences

Normal Path: User successfully views interview logs
Preconditions • User must log into the provided web app
Interactions • The user clicks "View Logs" button
Post conditions • Logs are displayed • Afterwards, the user can click on the "Return" button to return to home screen
Categorization • Criticality: High • Probability of Defects: Low • Risk: Medium

Exceptional Path: An error message is displayed
Preconditions • Unable to retrieve logs
Interactions • An exception is thrown in the system.
Postconditions • Error message is displayed
Categorization • Criticality: High • Probability of Defects: Low • Risk: High

Functional Requirement

REQ-21 The web app shall enable users to view interview logs.

REQ-22 The web app shall enable the user to return to the home screen.

REQ-23 In case, users sign out of the web app, the user shall only be able to use the web app's functionality once the user has signed back into the web app after providing email address & password, as input to the web app.

Functional Requirements with Traceability information

Table 3 REQ 1

Requirement ID	REQ-1		**Requirement Type**	Functional		**Use Case**	UC1	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	-							
Description	The web app shall enable users to get themselves registered with the system							
Rationale	This is required to support multiple interviewees on a single system							
Source	-				**Source Document**	-		
Acceptance/Fit Criteria	User is able to register themselves successfully							
Dependencies	Credentials must be stored and available at all times							
Priority	**Essential**	✓	**Conditional**			**Optional**		
Change History	-							

Table 4 REQ 2

Requirement ID	REQ-2	**Requirement Type**	Functional	**Use Case**	UC1

Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	-							
Description	The web app shall take user's credentials including name, email address, and password							
Rationale	This is required to support multiple interviewees on a single system							
Source	-				**Source Document**	-		
Acceptance/Fit Criteria	User is able to enter credentials successfully							
Dependencies								
Priority	**Essential**	✓	**Conditional**			**Optional**		
Change History	-							

Table 5 REQ 3

Requirement ID	REQ-3		**Requirement Type**	Functional		**Use Case**	UC1	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-2							
Description	The web app shall authenticate user's input data by matching verification code with the system's database							
Rationale	This is required to support multiple interviewees on a single system							

Source	-			**Source Document**	-			
Acceptance/Fit Criteria	User is able to authenticate successfully							
Dependencies	Credentials must be stored and available at all times							
Priority	**Essential**	✓	**Conditional**		**Optional**			
Change History	-							

Table 6 REQ 4

Requirement ID	REQ-4		**Requirement Type**	Functional	**Use Case**	UC1		
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-3							
Description	Only, in case of successful authentication, the web app shall take the user to the home screen							
Rationale	This is required to authenticate user due to the sensitive nature of the data							
Source	-			**Source Document**	-			
Acceptance/Fit Criteria	User is able to authenticate successfully before redirecting to home screen							
Dependencies	-							
Priority	**Essential**	✓	**Conditional**		**Optional**			
Change History	-							

Table 7 REQ 5

Requirement ID	REQ-5		Requirement Type	Functional		Use Case	UC1	
Status	New	✓	Agreed-to		Baselined		Rejected	
Parent Requirement	REQ-4							
Description	In case, user signs out of the web app, user shall only be able to use web app's functionality once user has signed back into the web app after providing email address & password, as input to the web app							
Rationale	This is required to authenticate user due to the sensitive nature of the data							
Source	**-**				Source Document	**-**		
Acceptance/Fit Criteria	User is required to login again once they have logged out							
Dependencies	-							
Priority	Essential	✓	Conditional			Optional		
Change History	**-**							

Table 8 REQ 6

Requirement ID	REQ-6		Requirement Type	Functional		Use Case	UC2	
Status	New	✓	Agreed-to		Baselined		Rejected	
Parent Requirement	REQ-4							

Description	The web app shall enable users to enter and save interviewee information into the system					
Rationale	This is required to add information of the interviewee					
Source	-			**Source Document**	-	
Acceptance/Fit Criteria	User is able to add the required information successfully					
Dependencies	-					
Priority	**Essential**	✓	**Conditional**		**Optional**	
Change History	-					

Table 9 REQ 7

Requirement ID	REQ-7		**Requirement Type**	Functional		**Use Case**	UC2	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-4							
Description	The web app shall take interviewee's credentials including name, gender, and age as input							
Rationale	This is required to add information of the interviewee							
Source	-				**Source Document**	-		
Acceptance/Fit Criteria	User is able to add the required information successfully							

Dependencies	-						
Priority	**Essential**	✓	**Conditional**		**Optional**		
Change History	**-**						

Table 10 REQ 8

Requirement ID	REQ-8		**Requirement Type**	Functional		**Use Case**	UC2	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-4							
Description	The web app shall authenticate user's input data by matching valid characters with the system's database							
Rationale	This is required to validate the information of the interviewee							
Source	**-**				**Source Document**	**-**		
Acceptance/Fit Criteria	User has not entered any special character							
Dependencies	-							
Priority	**Essential**	✓	**Conditional**			**Optional**		
Change History	**-**							

Table 11 REQ 9

Requirement ID	REQ-9	**Requirement Type**	Functional	**Use Case**	UC2

Status	New	✓	Agreed-to		Baselined		Rejected	
Parent Requirement	REQ-8							
Description	Only, in case of successful validation, the web app shall take the user to the calibration screen							
Rationale	This is required to validate the information of the interviewee							
Source	-				Source Document	-		
Acceptance/Fit Criteria	User has not entered any special character							
Dependencies	-							
Priority	Essential	✓	Conditional			Optional		
Change History	-							

Table 12 REQ 11

Requirement ID	REQ-11		Requirement Type		Functional	Use Case	UC2	
Status	New	✓	Agreed-to		Baselined		Rejected	
Parent Requirement	REQ-9							
Description	The web app shall enable users to start a calibration session							
Rationale	This is required to calibrate the equipment							
Source	-				Source Document	-		

Acceptance/Fit Criteria	User is able to start a calibration session						
Dependencies	-						
Priority	**Essential**	✓	**Conditional**		**Optional**		
Change History	**-**						

Table 13 REQ 12

Requirement ID	REQ-12		**Requirement Type**	Functional		**Use Case**	UC2	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-11							
Description	The web app shall validate inputs from hardware							
Rationale	This is required to check the hardware							
Source	**-**				**Source Document**	**-**		
Acceptance/Fit Criteria	Web App is able to validate inputs from hardware							
Dependencies	Hardware must be connected to the local machine							
Priority	**Essential**	✓	**Conditional**			**Optional**		
Change History	**-**							

Table 14 REQ 13

Requirement ID	REQ-13		**Requirement Type**	Functional		**Use Case**	UC2	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-12							
Description	The web app shall calculate average blinks of the interviewee							
Rationale	This is required for prediction in later stage							
Source	**-**				**Source Document**	**-**		
Acceptance/Fit Criteria	Web App is able to calculate average blinks of the interviewee							
Dependencies	Hardware must be connected to the local machine							
Priority	**Essential**	✓	**Conditional**			**Optional**		
Change History	**-**							

Table 15 REQ 14

Requirement ID	REQ-14		**Requirement Type**	Functional		**Use Case**	UC2	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-13							
Description	Only, in case of successful calibration, the web app shall take the user to the interview screen							

Rationale	This is required to uniquely calibrate the system on every interviewee							
Source	-			**Source Document**	-			
Acceptance/Fit Criteria	Web App is able to calibrate the system successfully							
Dependencies	Hardware must be connected to the local machine							
Priority	**Essential**	✓	**Conditional**		**Optional**			
Change History	-							

Table 16 REQ 16

Requirement ID	REQ-16		**Requirement Type**	Functional	**Use Case**	UC2		
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-14							
Description	The web app shall enable users to start and end the interview							
Rationale	This is required to conduct the interview							
Source	-			**Source Document**	-			
Acceptance/Fit Criteria	User is able to start and end the interview							
Dependencies	Hardware must be connected to the local machine							
Priority	**Essential**	✓	**Conditional**		**Optional**			

Change History	-

Table 17 REQ 17

Requirement ID	REQ-17		**Requirement Type**	Functional		**Use Case**	UC2
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**
Parent Requirement	REQ-16						
Description	The web app shall read input values from the hardware during the session						
Rationale	This is required to conduct the interview						
Source	-				**Source Document**	-	
Acceptance/Fit Criteria	Web App is able to read the input values of the hardware						
Dependencies	Hardware must be connected to the local machine						
Priority	**Essential**	✓	**Conditional**			**Optional**	
Change History	-						

Table 18 REQ 18

Requirement ID	REQ-18		**Requirement Type**	Functional		**Use Case**	UC2
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**
Parent Requirement	REQ-17						

Description	The web app shall process the input values to display an output					
Rationale	This is required to predict the output					
Source	-			**Source Document**	-	
Acceptance/Fit Criteria	Web App is able to process and predict an output					
Dependencies	Hardware must be connected to the local machine					
Priority	**Essential**	✓	**Conditional**		**Optional**	
Change History	-					

Table 19 REQ 19

Requirement ID	REQ-19		**Requirement Type**	Functional		**Use Case**	UC2	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-18							
Description	Only, in case of successful processing, the web app shall take the user to the home screen							
Rationale	This is required to ensure completion of the interview							
Source	-				**Source Document**	-		
Acceptance/Fit Criteria	Web App is able to finish the processing successfully							

Dependencies	Hardware must be connected to the local machine					
Priority	**Essential**	✓	**Conditional**		**Optional**	
Change History	**-**					

Table 20 REQ 21

Requirement ID	REQ-21		**Requirement Type**	Functional		**Use Case**	UC1	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-4							
Description	The web app shall enable users to view interview logs							
Rationale	This is required to view history of interviews							
Source	**-**				**Source Document**	**-**		
Acceptance/Fit Criteria	Web App is able to display the logs							
Dependencies	-							
Priority	**Essential**	✓	**Conditional**			**Optional**		
Change History	**-**							

Table 21 REQ 22

Requirement ID	REQ-22		**Requirement Type**	Functional		**Use Case**	UC1	
Status	**New**	✓	**Agreed-to**		**Baselined**		**Rejected**	
Parent Requirement	REQ-21							
Description	The web app shall enable the user to return to the home screen							
Rationale	This is required to direct the user back to the home screen after viewing the logs							
Source	-				**Source Document**	-		
Acceptance/ Fit Criteria	User is able to return to the home screen							
Dependencies	-							
Priority	**Essential**	✓	**Conditional**			**Optional**		
Change History	-							

Non-functional Requirements & Software System Attributes

Performance Requirements

Response Time

The 95% of response time of the system shall be less than 10 seconds excluding browser render time.

Workload

The system should be able to support 1 request at a time.

Availability

NFR-1 The system shall always be available to receive command from the user and to start a session.

Reliability

NFR-2 The Web App shall always show the latest and complete set of interview logs.

Maintainability

NFR-3 The system shall use a standard EEG headset, webcam, and different components available in the market, which may be replaced in case of component failure.

NFR-4 User Interface shall be independent of the backend code responsible for interacting with hardware components, therefore, allowing changes to be done in either of the codes without affecting the other.

Security

NFR-5 Web App shall not allow users to use application or system features unless registered and signed in.

NFR-6 The Web App shall not require the user to sign into the application each time except for the first time unless the user signs out.

Usability

NFR-9 The user shall be able to use a web app with a maximum of three training sessions.

NFR-10 User guide shall be provided within the web app.

NFR-11 The graphical user interface of the system shall be designed with usability as the priority. The web app will be presented and organized in a manner that is both visually appealing and easy to use.

Project Design & Architecture

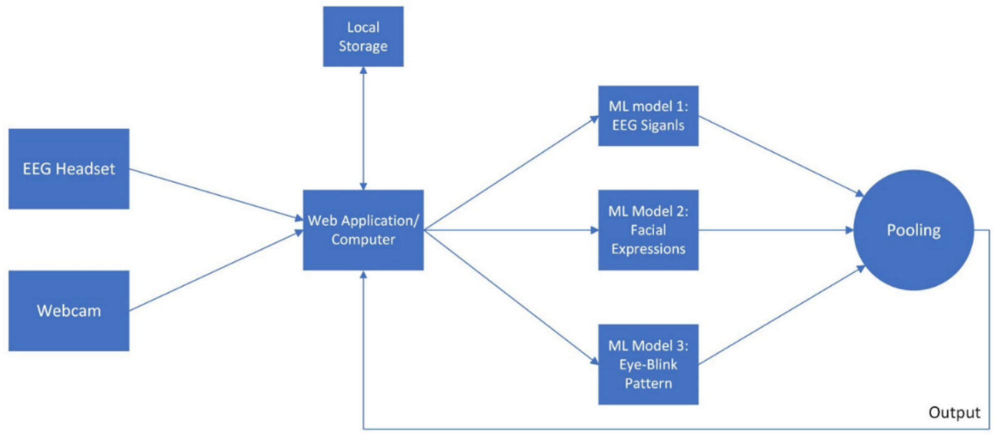

Figure 7 Architectural Model Used (Data Flow Model)

Why We Chose Data Flow Architecture

We chose a Data-Flow Architecture for NeuraLie after a thorough comparison between available architectures and industry standards for applications that are heavily dependent on data manipulation and processing. As can be seen in the data flow architecture diagram in the previous section, a series of transformations on consecutive sets of input data is to be done, where data and operations are independent of each other. Data enters the system and flows through the modules until they are assigned to some final destination (output or local storage). This layout is indicative of systems that would benefit from a data-flow architecture. The data transformation process in this system follows the pipe and filter approach, where data is incrementally transformed by a series of components. This approach is characterized by the flow of data driven by the data itself and involves dividing the system into components such as data sources, filters, and pipes. Some advantages of this approach are that it provides/supports concurrency and high throughput for excessive data processing. It also provides reusability and simplifies system maintenance, along with flexibility, by supporting both sequential and parallel execution. One downside of using the data-flow architecture that is usually discussed in documentation is that the architecture does not work well for applications that require greater user engagement. Since NeuraLie will be functioning as a standalone application for individual lie detection test administrators, we will not be experiencing a large amount of user engagement at a time.

Module Identification

ML Models:

1. **EEG module**: uses EEG signals from the Nexstem headset as input and works initially with calibration inputs to adjust itself according to the EEG signals pattern of the subject.
2. **Facial Expressions module:** Analyzes consecutive images from the real-time video feed being obtained from the webcam and detects subtle changes in facial expressions.
3. **Eye-Blink Pattern module:** Counts the rate and frequency of the subject's eye blinks and makes decisions based on the researched observation that eye-blinking pattern varies with changing cognitive demand of the subject.

4. **Pooling:** The pooling module will take inputs from each of the 3 ML models and process them into a single output which will be the basis for the system's final decision.
5. **Data Storage:** For the storage of logs, local storage will be used since separate databases are not a necessity.
6. **Login:** Each system can have multiple users/interviewers who will have a private log of their conducted interviews saved locally. This will be accessible through valid login credentials.
7. **Calibration:** The calibration module will be used when setting up NeuraLie for a new subject that has not previously taken the test/interview. The calibration is necessary for the system to get some base EEG signals and facial expressions to compare against the data of the actual interview. Some buffer questions are asked
8. **Testing/Interview:** This module will be the interview where questions will be asked, responses will be evaluated by NeuraLie, and an output will be given for each response.

4+1 Architecture View Model

Use Case View

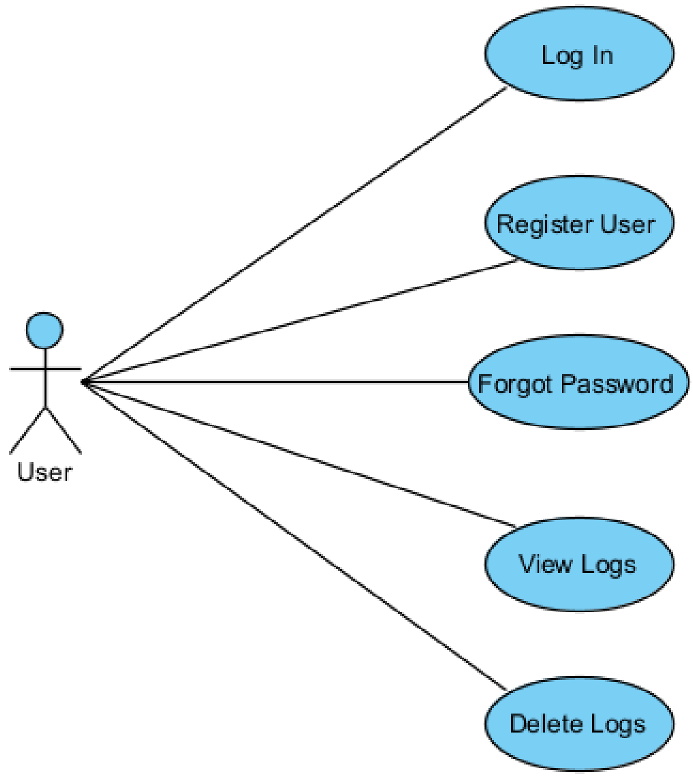

Figure 8 UC1: Viewing and Deleting Logs

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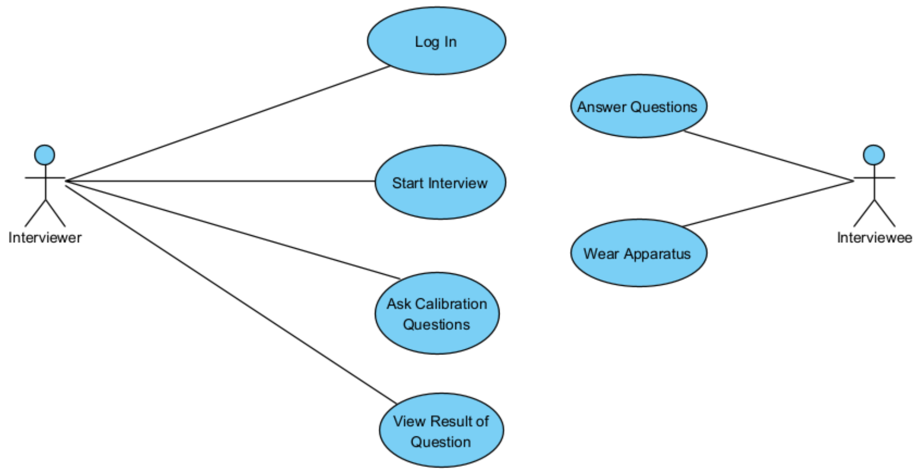


Figure 9 UC2: Conducting Interview

Logical View (State Machine)

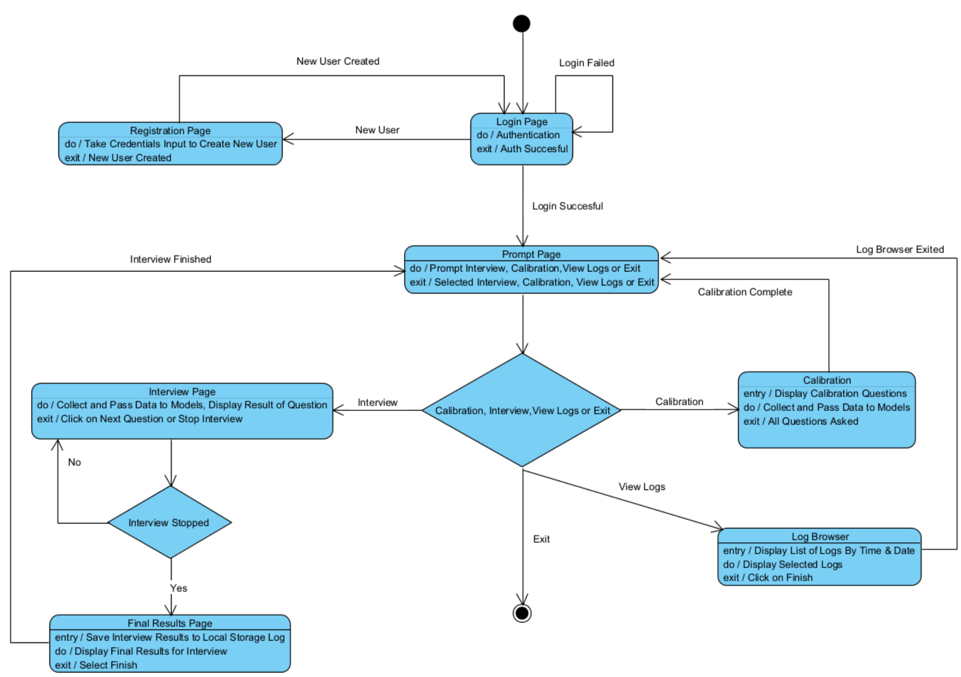


Figure 10 Logical View (State Machine)

Development View (Component Diagram)

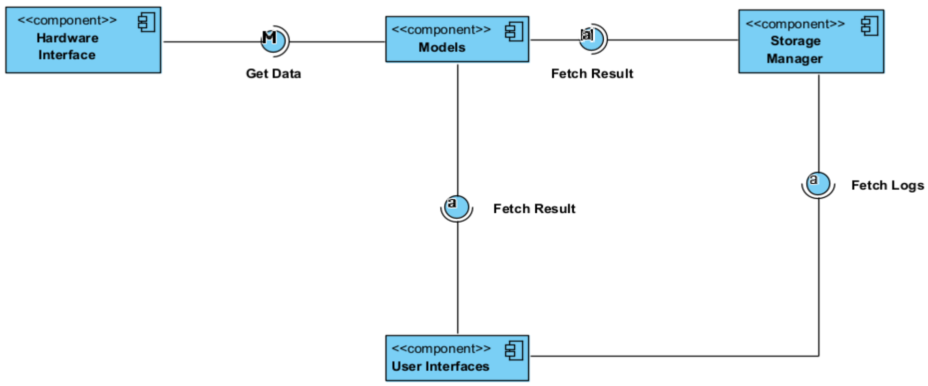


Figure 11 Development View (Component Diagram)

Process View (Sequence Diagram)

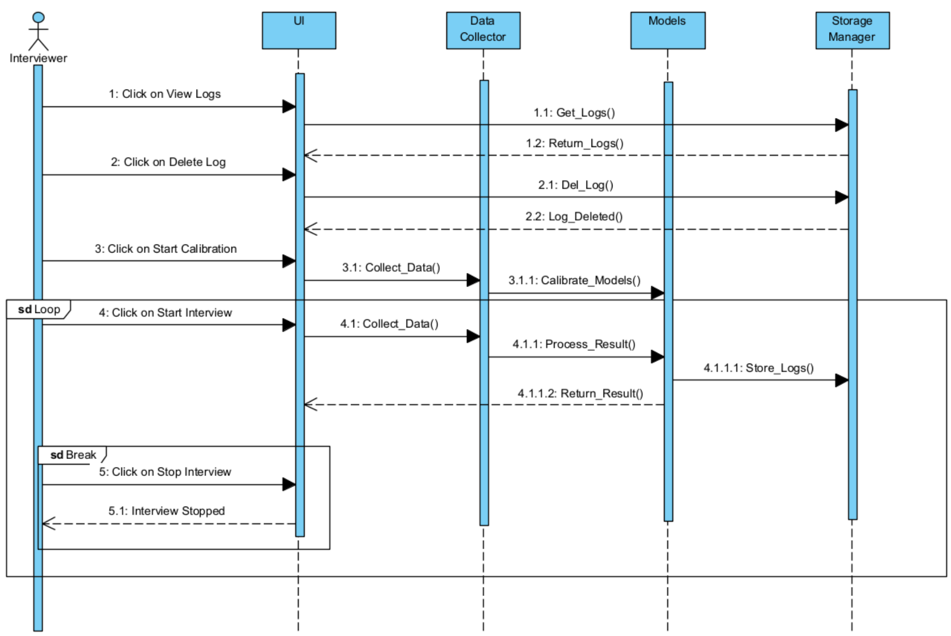


Figure 12 Process View (Sequence Diagram)

Physical View (Deployment Diagram)

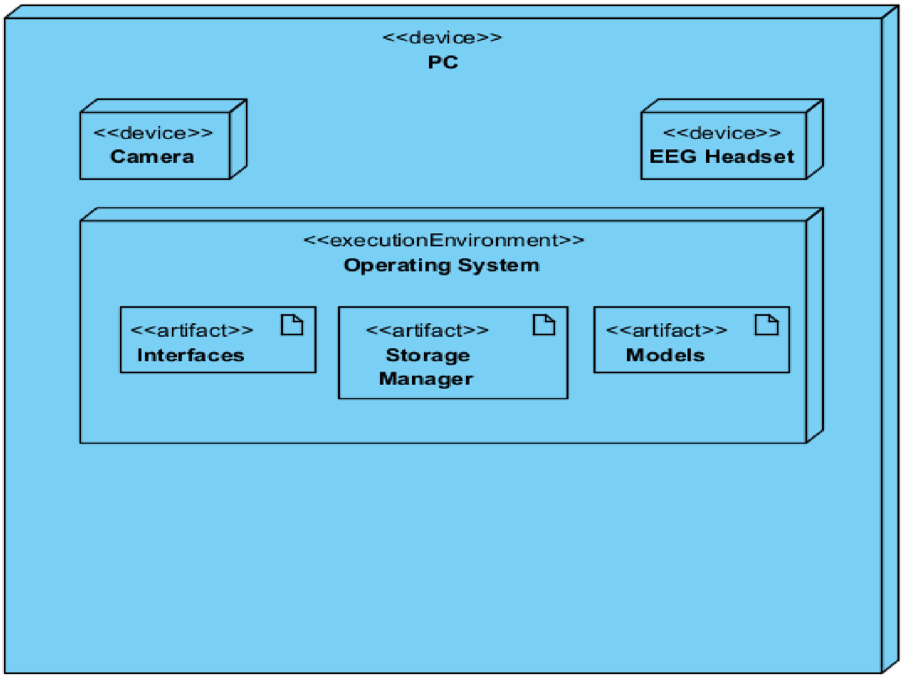


Figure 13 Physical View (Deployment Diagram)

User Interface Design

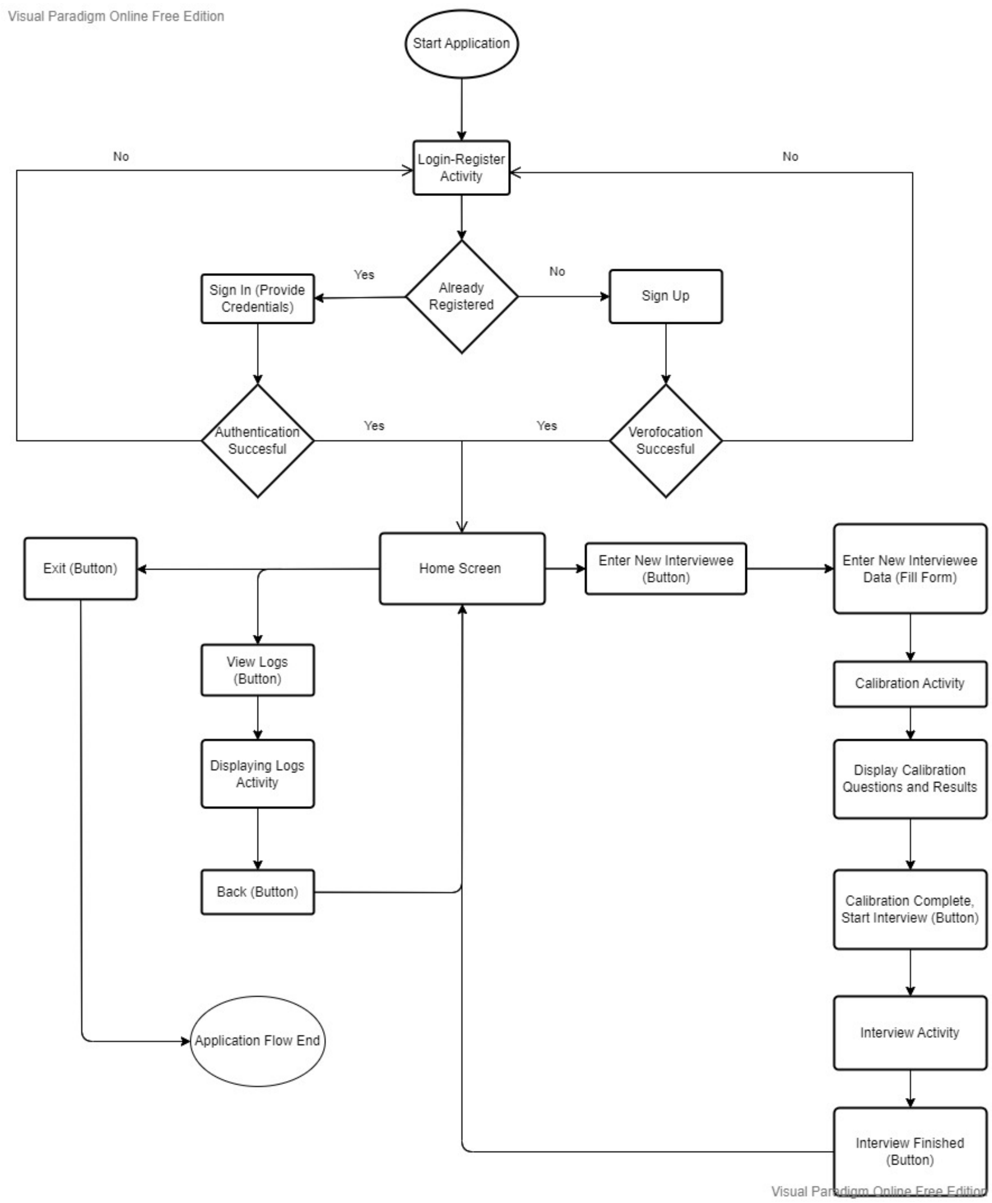


Figure 14 UI Flowchart

Chapter 4: Proposed Solution (Methodology, Implementation)

Methodology

Work breakdown structure

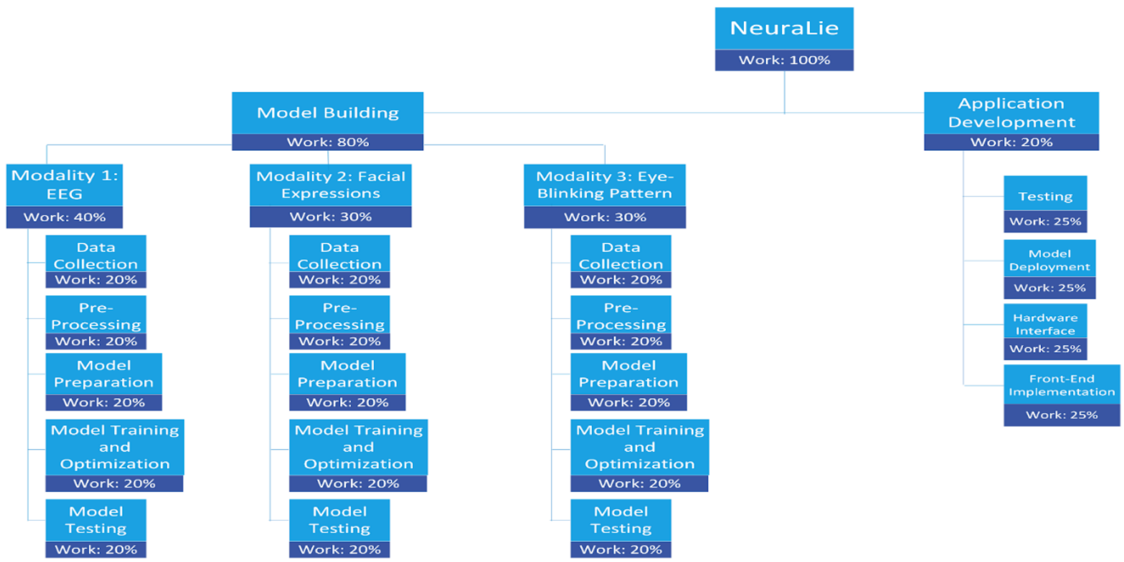


Figure 15 Work Breakdown Structure

Implementation

The EEG Module

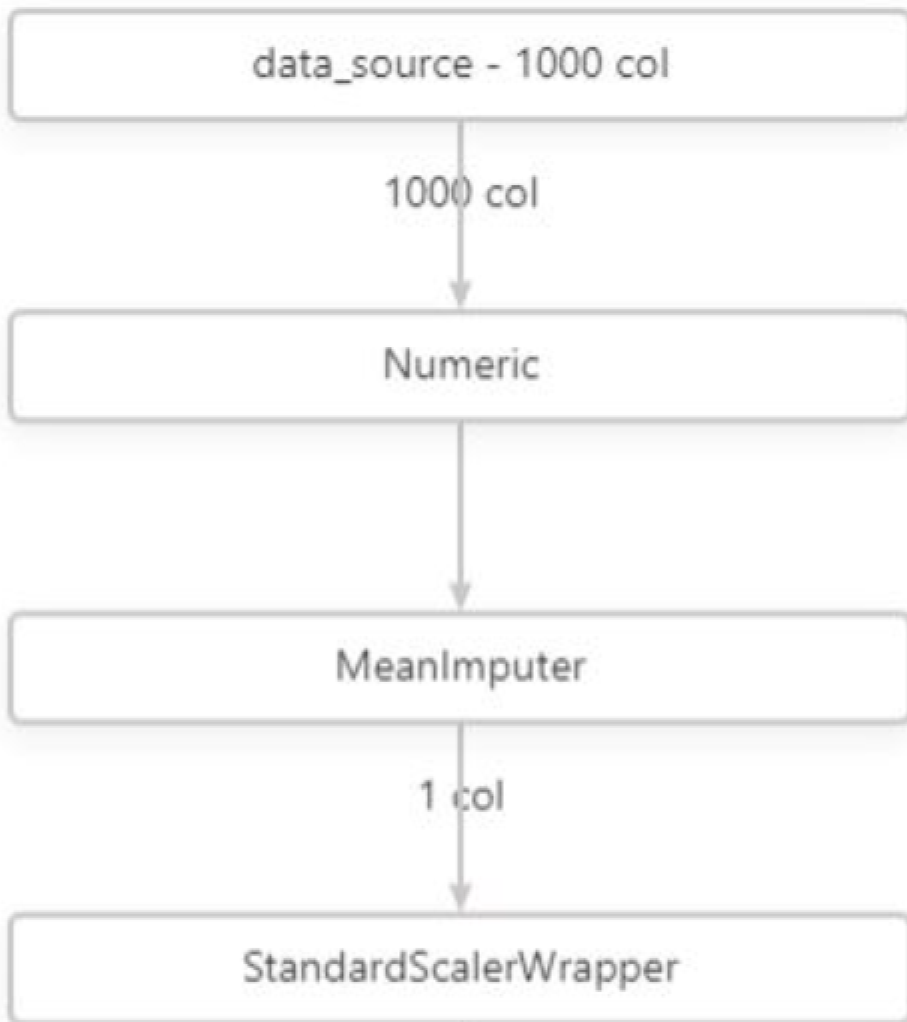


Figure 16 EEG Preprocessing

The EEG Module had the alpha input from the dataset that was a total of 1000 columns. It was to be noted that all of these were numerical values, and some of the data items did not have values for the complete 1000 columns because the answer of the interviewee ended before the 1000 columns time span. Hence the need for using the mean imputer module arises.

The mean imputer is a very popular data processing and cleaning technique which is used to fill in missing values in a dataset. The mean imputer replaces the missing values in the data set by computing the average of the mean value of the feature (column) where missing value is found.

The next processing step is to wrap the input dataset in a standard scaler wrapper, also known as Z-score normalization. It involves the transformation of the data set such that the mean is 0 and the standard deviation is one. This technique is useful because it helps to ensure that the features of the dataset are similar on a scale and have less variance, which can improve the performance of machine learning algorithms.

The last step after pre-processing the data was to distribute the dataset into it's appropriate section. We decided to distribute the dataset into 3 sections as per the details provided in the table below.

Table 22 Split

Data Set Categories	Percentage of Data
Training Data Set	80%
Validation Data Set	10%
Testing Data Set	10%

The next step was to finally implement the machine learning model since all the preprocessing was already taken care of. Since the dataset for EEG Module was not too extensive, we decided to initially experiment with the classical machine learning approaches that we have and obtain a decent enough accuracy. Multiple machine learning models were tried and experimented for the binary classification as per the need of the problem. The ones with the top metrics are provided in the sections to follow.

Eye blinking patterns

In our study, we investigated the efficacy of blink patterns as a modality for deception detection. We began by extracting blink patterns from a dataset of videos where subjects either lied or told the truth. To accomplish this, we used OpenCV and facial landmarks to detect when the subject blinked and calculated a running average of blinks over time.

Once we recorded the blink patterns for the entire dataset, we trained various machine learning models on the prepared data. SVMs, CNNs, and LSTMs were unable to produce satisfactory results. However, after experimenting with multiple models, we found that XGBoost produced promising results.

To prepare the data for the XGBoost model, we utilized standard scalar normalization and KNN imputer to fill in missing values.

Facial Expressions

The facial expressions modality makes use of facial emotions and their change over time in a subject to detect deception. The dataset we have used for this modality is a combined dataset that comprises of a publicly available dataset used by a previous paper "Deception detection in videos", in AAAI 2018 [8] which contains real life trial videos and a dataset we formulated on our own wherein 7 students of GIK Institute were interviewed and asked 14 questions each, resulting in 14 videos each.

For this modality we used transfer learning from a pre-trained facial expression recognition (FER) model which achieved 66.4% accuracy on test dataset, so this model performance is good enough as a baseline, considering that the Kaggle competition winner had an accuracy of 77.1%.

For preprocessing, we take in a video, split it into 300 frames (10 seconds of video), then encode each of those frames with a labelled emotion from 0-6 using the FER. This time-stacked data is then used by 2-layer uni-directional GRU that detects patterns in the time-series data.

Combining the modules

For combining the modules we shall be using a threshold based ensemble method where multiple classes are combined to make a prediction. In our approach we use two models where the first model is a threshold model and the second model is a fallback model which is also termed as . This approach is very suitable when models have strengths and weaknesses and one needs to capitalize on the strengths and minimize the weaknesses, leading to more accurate and robust predictions.

Front End Module

Django is a high-level framework used for building web-based applications. It is a Python based framework which helps provide a standardized way to develop web applications. Django offers complex features such as URL Routing, Template Rendering, Database Modelling, and authentication which not only makes it a very easy to useful tool but also a go to option. Django offers a wide range of advantages to its end users like rapid development, scalability, security, a large community for FAQs and help, and the versatility of the framework to produce applications as simple as blog to applications as complex as social networks.

Chapter 5: Results and Discussion

Here, we present the experimental outcomes of all the distinct algorithmic approaches we have attempted along with displaying how the modalities tie together through NeuraLie's web application, which contains it's own host of features. To evaluate performance, we have used precision as our primary metric along with accuracy. The confusion matrices are also shown.

For the EEG Modality we first extracted a time based signal from the EEG Output of the helmet where the subject is either lying or telling the truth. After the preprocessing done as explained in the methodologies part of the report we experimented several classical machine learning techniques to obtain good results. For the evaluation of this modality again precision and accuracy are two of the most important metrics which we will be looking forward towards while we evaluate our models.

First and foremost, we tried classifying our binary classification problem with XG Boost Classifier. XG Boost is a popular open source machine learning library which is widely used for classification problems. XG Boost gave the outputs which were a combination of 0.6875 for accuracy and a precision of 0.71.

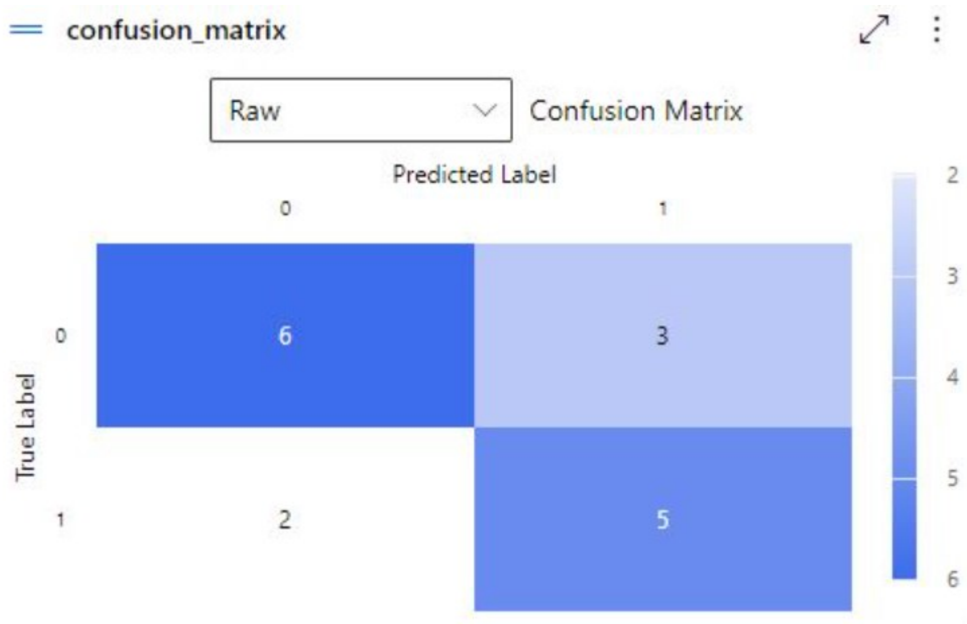


Figure 17 XGBoost

The next model which should promising results and the best ones through out our experiments was the K – Nearest Neighbor. KNN is another simple yet effective machine learning algorithm which gave us a combination of accuracy of 0.75 and a precision of 0.86 as well.

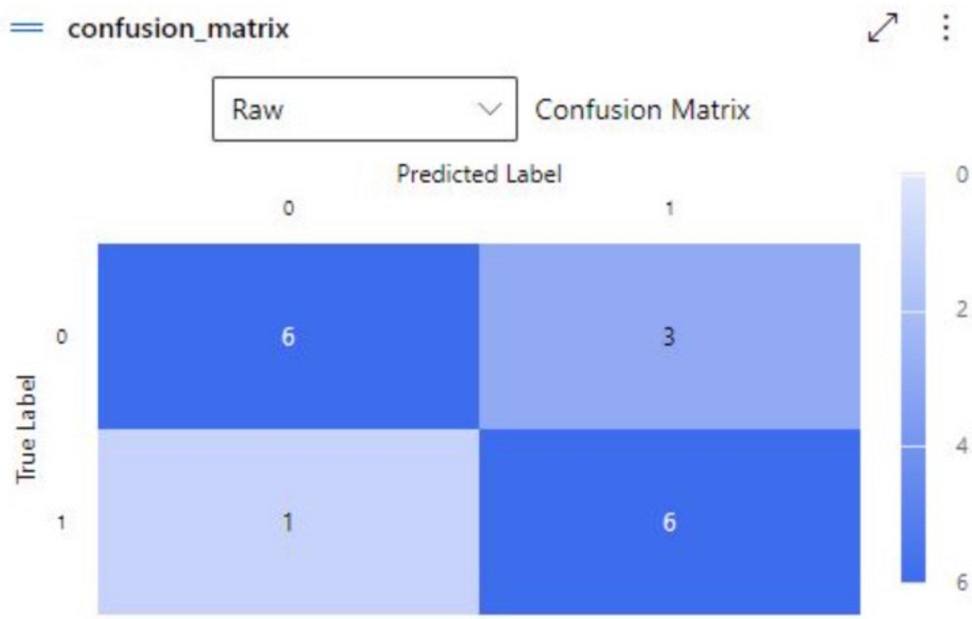
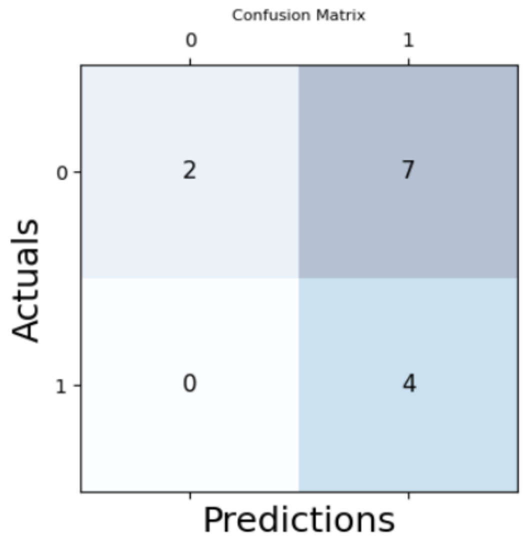


Figure 18 KNN

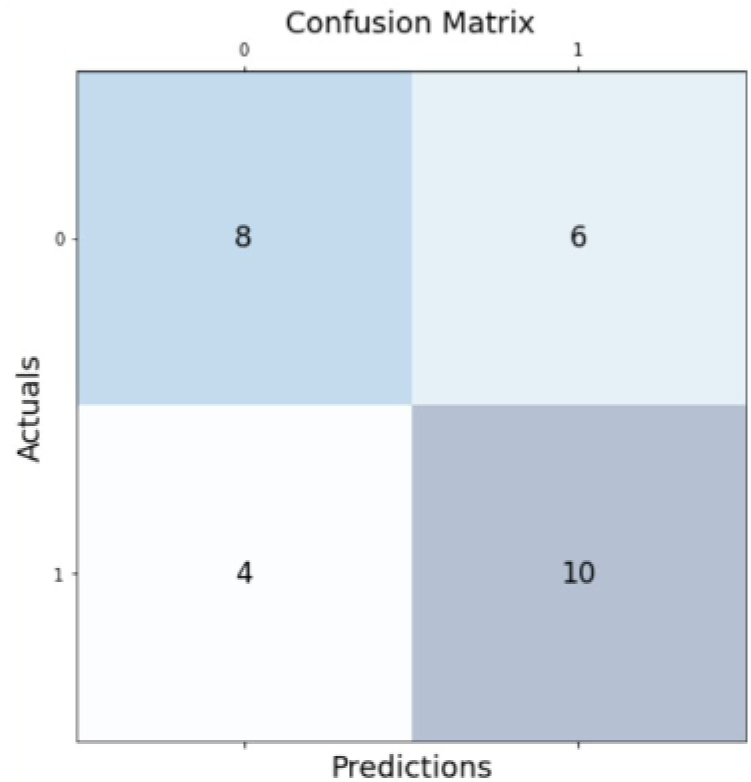
For the facial expressions modality, initially, we attempted to utilize a 3-dimensional CNN design for identifying facial expressions. We hoped that our 3-D filters would capture significant "tells" of deceit in videos by considering the 2-dimensional image, the third dimension being time. In this design, we did not make use of any transfer learning from FER. The input underwent eight Conv3D layers, interspersed with max-pooling layers and dropouts, before being fed through four fully-connected dense layers that result in a sigmoid activation, which produces truth or lie predictions. Evaluation metrics used were binary cross-entropy loss, Adam optimizer, and binary accuracy. Despite training for 100 epochs and using a small batch size of 5 due to memory constraints, the model's test accuracy was only 46%. Additionally, the model's performance varied with each training, implying that it is not a reliable predictor.



	precision	recall	f1-score	support
0	1.00	0.22	0.36	9
1	0.36	1.00	0.53	4
accuracy			0.46	13
macro avg	0.68	0.61	0.45	13
weighted avg	0.80	0.46	0.42	13

Figure 19 Conv3D

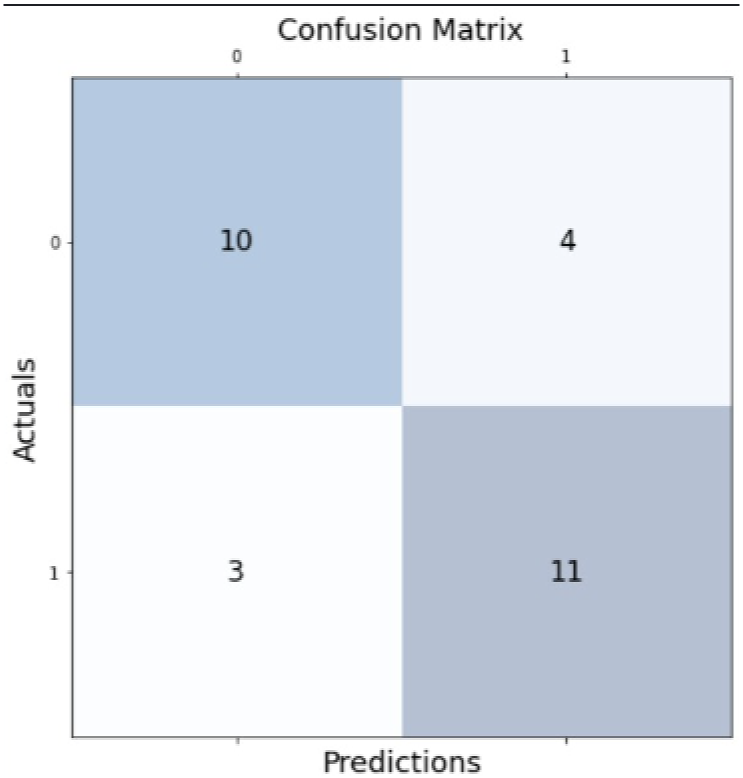
As an alternative approach, we constructed a GRU model with two layers of uni-directional Gated Recurrent Units (GRU) to detect patterns in time series data after passing the input through Conv1D and MaxPooling layers. We selected two layers of GRU since they are sufficient for detecting intricate patterns in data without sacrificing performance. Adding more layers of GRU-based layers only harmed performance. The following confusion matrix shows the results of this model.



	precision	recall	f1-score	support
0	0.67	0.57	0.62	14
1	0.62	0.71	0.67	14
accuracy			0.64	28
macro avg	0.65	0.64	0.64	28
weighted avg	0.65	0.64	0.64	28

Figure 20 GRU

For the eye-blinking pattern modality, To prepare the data for the XGBoost model, we utilized standard scalar normalization and KNN imputer to fill in missing values. The XGBoost model achieved an accuracy of 0.75 and F-1 scores of 0.74 for lies and 0.76 for truth.



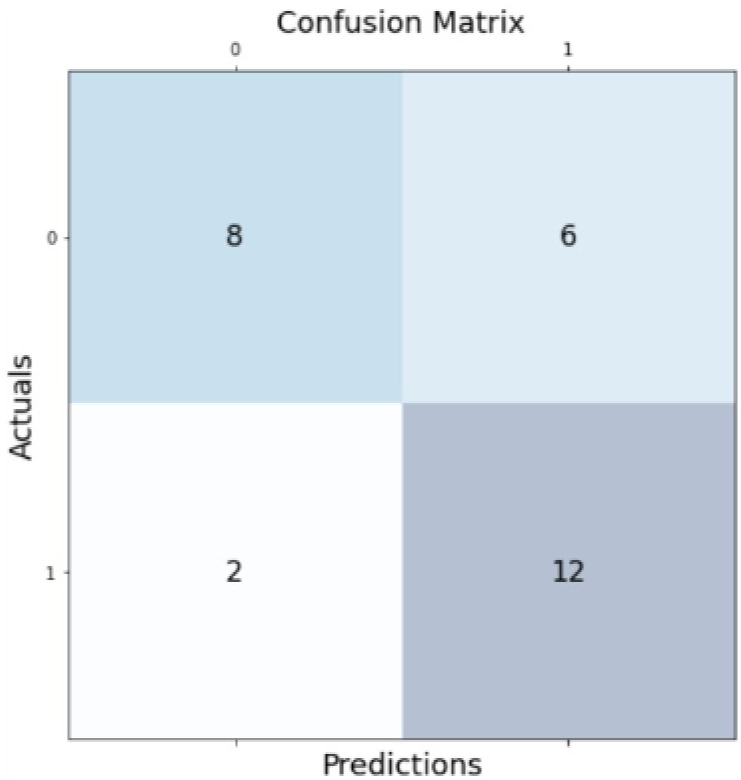
	precision	recall	f1-score	support
0	0.77	0.71	0.74	14
1	0.73	0.79	0.76	14
accuracy			0.75	28
macro avg	0.75	0.75	0.75	28
weighted avg	0.75	0.75	0.75	28

Figure 21 Eye-Blinks

For pooling the results of the three models together, we have used a method which is a type of threshold-based ensemble method, where multiple models are used to make a prediction and a threshold is used to determine which model's prediction to use. Specifically, in our approach, the first model is used as a threshold model and the second model is used as a fallback model.

The first model being the eye-blinking pattern model and the second one being the facial expressions recognition model. This type of approach is sometimes called a cascaded classifier or a hierarchical classifier.

We first check the output probability of the eye-blinking model. If the probability is greater than 0.6, then the prediction is 1, otherwise we move to the facial expressions recognition model for a conclusive result. Here is the confusion matrix when we use NeuraLie with this ensemble technique:



	precision	recall	f1-score	support
0	0.80	0.57	0.67	14
1	0.67	0.86	0.75	14
accuracy			0.71	28
macro avg	0.73	0.71	0.71	28
weighted avg	0.73	0.71	0.71	28

Figure 22 Results After Ensemble

Finally, for our web application built on Django, here are the screenshots from the running application:

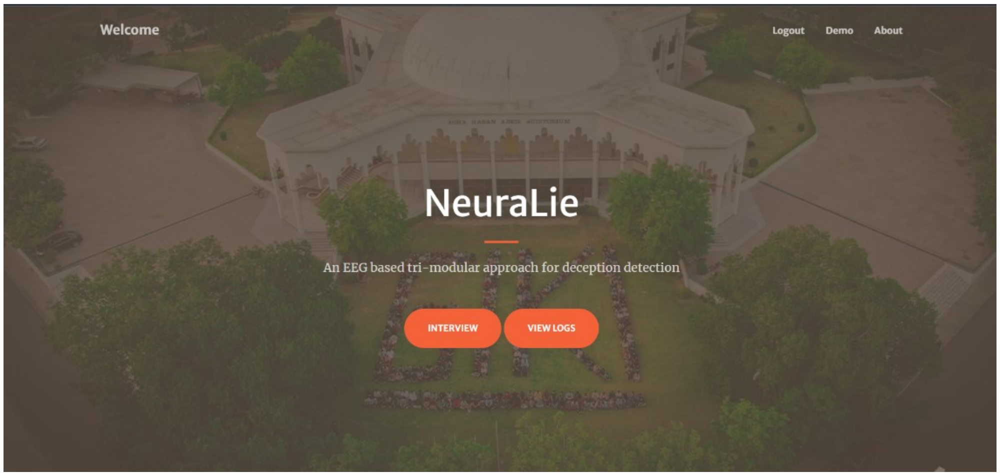


Figure 23 Home page

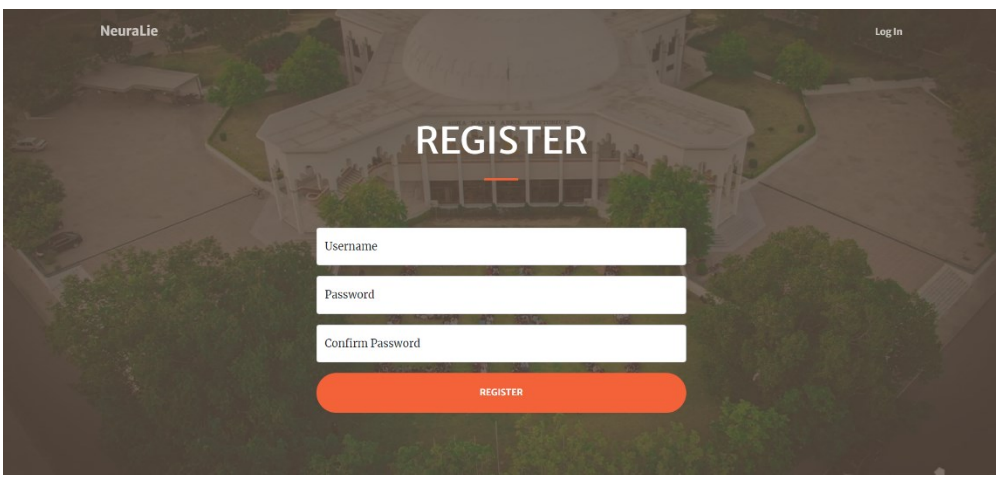


Figure 24 Register Page

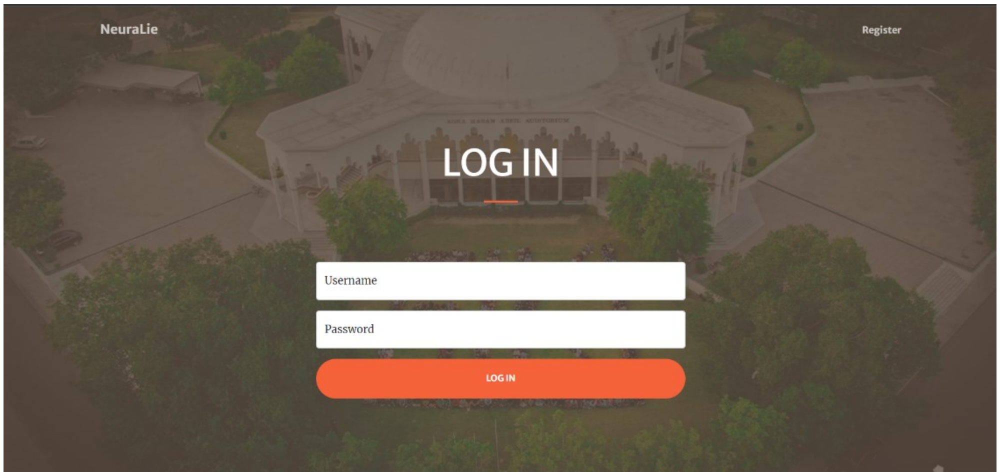


Figure 25 Login Page

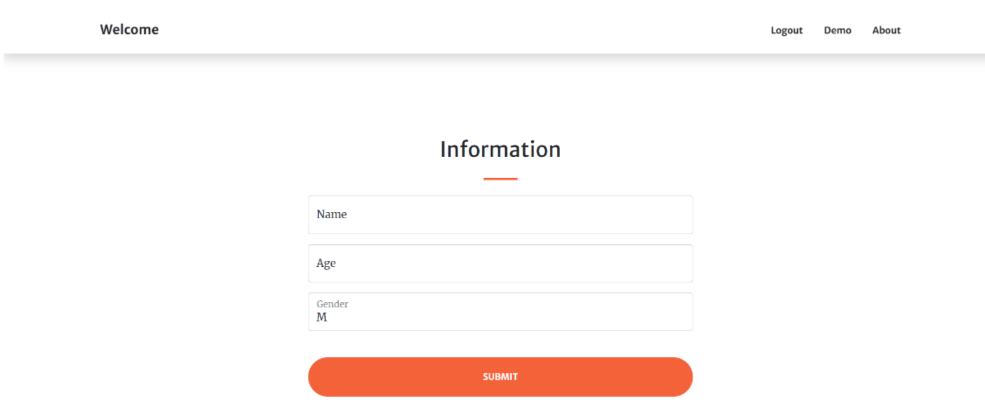


Figure 26 Interview Form

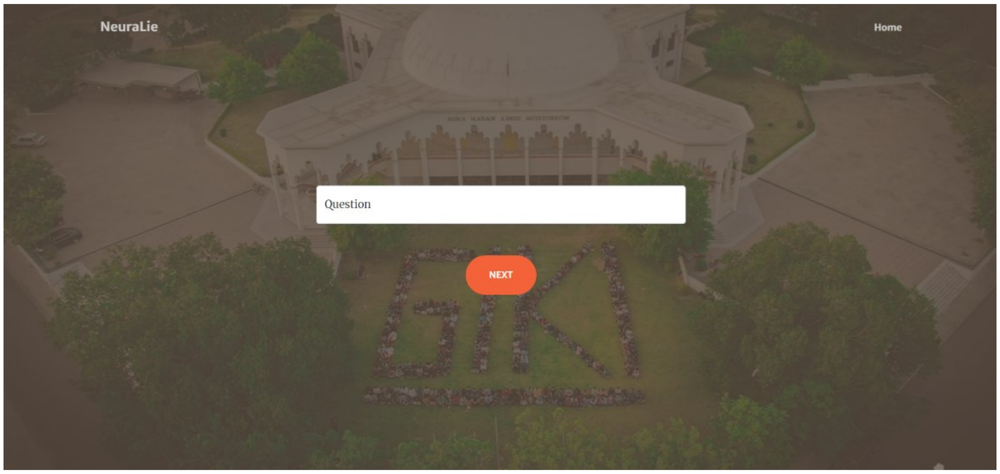


Figure 27 Question

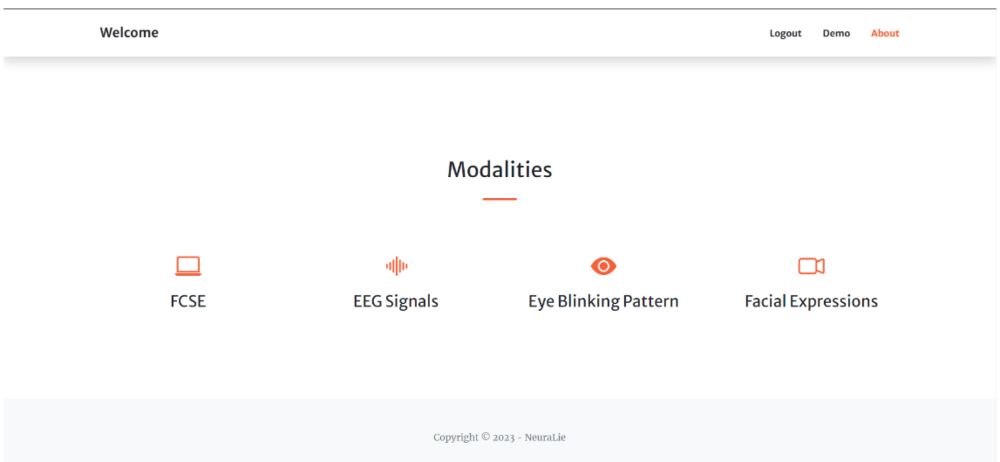


Figure 28 About

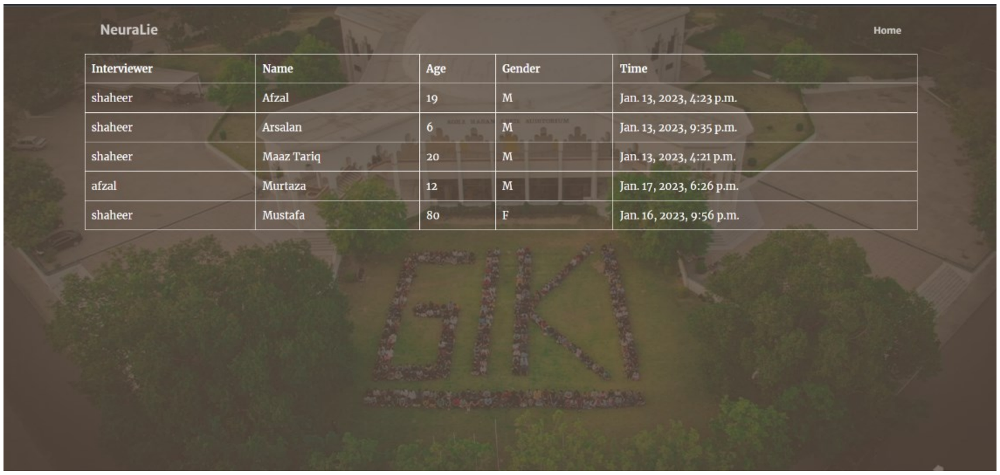


Figure 29 Logs

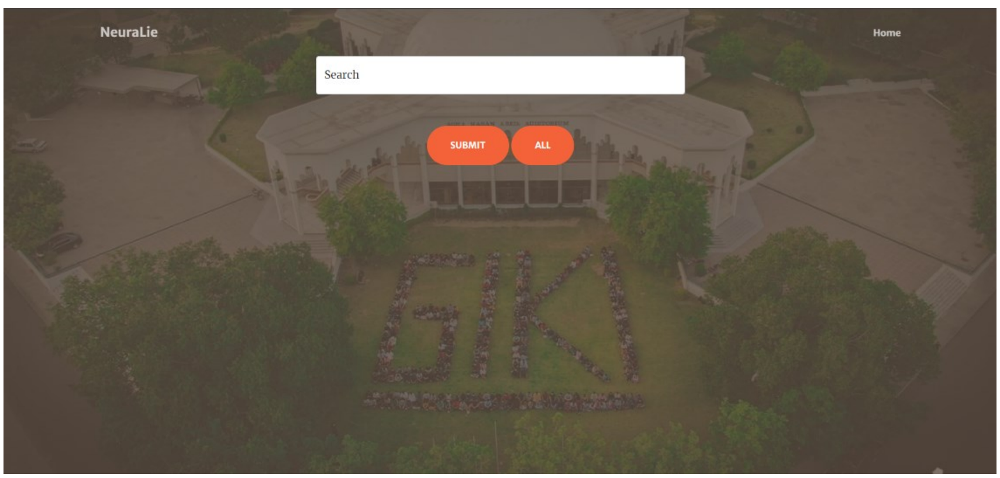


Figure 30 Log Search

Figure 31 Detailed Log

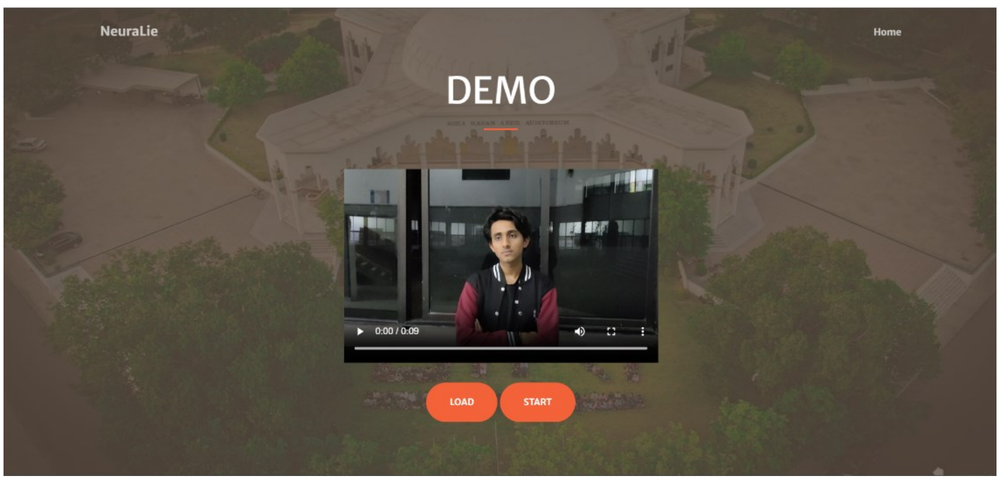


Figure 32 Demo

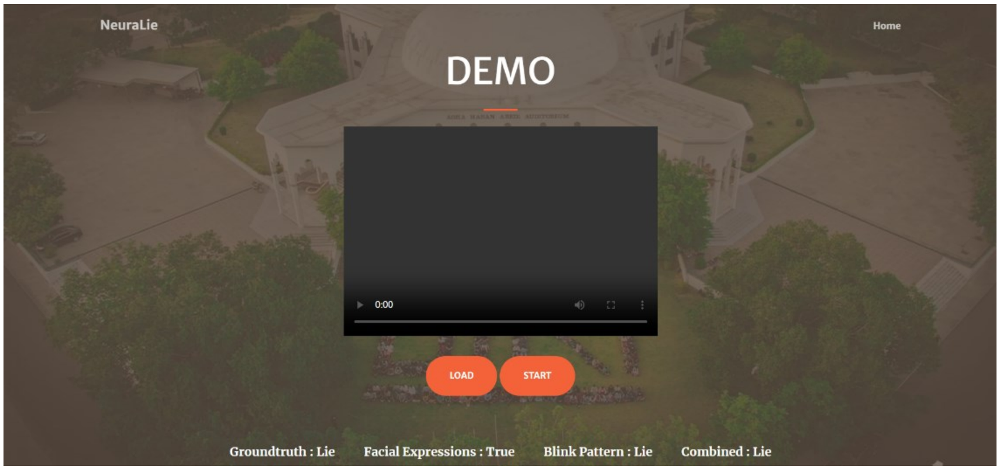


Figure 33 Demo Result

Chapter 6: Conclusion and Future Work

The field of deception detection has garnered significant attention from researchers, practitioners, and policymakers alike. Numerous modalities have been proposed, and extensive research has been conducted to enhance the accuracy and reliability of deception detection systems. Our study adds to the existing body of knowledge by evaluating various approaches and identifying their strengths and weaknesses.

The EEG Modality has already displayed satisfactory results for the industry standards as far as lie detection is concerned. However, with the ever-changing world there is always room for improvement. For this project we have only used the alpha band values from the EEG Data, to improve the reliability and to incorporate more frequency bands as input points from the EEG data for future work we can incorporate other EEG Input bands like Beta and Gamma bands to make the decision based on a larger variety of input bands rather than just one.

For the facial expressions recognition module, it is apparent that the model needs to show better performance in terms of the metrics achieved in order to be called viable. We believe that solely relying on emotions and their change over time stacked images is not sufficient to effectively deduce the difference between a lying subject and truthful one. So in terms of future work on this modality, we believe much more complex approaches like those of facial micro-expression recognition using machine learning instead of deep learning models may be necessary.

For the eye-blinking modality, our study demonstrates the feasibility of using blink patterns as a modality for deception detection, with promising results achieved using an XGBoost model. Our findings contribute to the existing body of knowledge on deception detection, and provide a foundation for future research in this field.

Our findings suggest that some modalities outperform others in terms of accuracy, while others require significant improvement. Additionally, we conclude that developing a viable deception detection technology for use in courtrooms and law enforcement is an ongoing endeavor that requires continued efforts. Although our technology may not be currently suitable for such applications, it provides a promising foundation for future developments.

The vast field of deception detection research demands a multidisciplinary approach, requiring collaboration between experts in psychology, linguistics, computer science, and other related fields. By employing diverse methodologies and techniques, researchers can explore the complexities of deceptive behavior and develop more effective detection systems.

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NeuraLie: An EEG-based Tri-Modal Approach for Deception Detection GHULAM ISHAQ KHAN INSTITUTE OF ENGINEERING SCIENCES AND TECHNOLOGY FACULTY OF COMPUTER SCIENCE AND ENGINEERING
(FCSE) Group Members: Muhammad Maaz Tariq - 2019342 Shaheer Alam

- 2019369 Mohammad Arslan – 2019306 Muhammad Afzal – 2019279 Advisors: Dr. Zahid Halim Engr. Ahsan Shah Engr. Talha Laique Certificate of Approval It is certified that the work presented in this report was performed by Muhammad Maaz Tariq, Mohmmad Arslan, Shaheer Alam, and Muhammad Afzal under the supervision of Dr. Zahid Halim, Engr. Ahsan Shah, Engr. Talha Laique. The work is adequate and lies within the scope of the BS degree in Computer Science/Computer Engineering at Ghulam Ishaq Khan Institute of Engineering Sciences and Technology. ------------------- Dr. Zahid Halim (Advisor) -------------------- Engr. Ahsan

Shah (Co-Advisor) -------------------- Dr. Ahmar Rashid (Dean) ------------------- Engr. Talha Laique (Co-Advisor) ABSTRACT NeuraLie is an AIbased lie detection solution that utilizes the subject's brain waves (EEG signals) along with other elusive physical cues, namely facial expressions and eye-blinking patterns, to detect deception. This particular approach not only aims to address the limitations and inaccuracies of the conventional polygraph but has also aimed to revolutionize the efficacy of lie detection systems in general. The conventional polygraph test uses only physiological responses making them less effective and unreliable, as has been proved over the years. NeuraLie will make use of an EEG headset and a camera, which will send inputs to the NeuraLie web application running on the computer they are connected to. The procedure will be the same as in current lie detection techniques, involving an examiner/interviewer and a subject being monitored by the hardware. The interviewers can get themselves registered, allowing multiple interviewers to make use of the same machine and have their own logs stored locally for future reference. The data collected from the two hardware interfaces, EEG headset, and camera, are sent for processing on the backend, after which they are given as input to the three Deep Learning models that NeuraLie utilizes. The results are ensembled to reach a conclusive result, which is a binary classification between truth and lies. This document explains the design, development, and comprehensive description of NeuraLie, which comprises three deep learning models and a web application for interacting with the system. ACKNOWLEDGEMENTS We would like to express our sincere gratitude to all the individuals who have contributed to the successful completion of this final year project. First and foremost, we would like to thank our project supervisors, Dr. Zahid Halim, Engr. Ahsan Shah, and Engr. Talha Laique for his invaluable guidance, support, and encouragement throughout the project. His vast knowledge, experience, and expertise have been instrumental in shaping