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Cognitive Trace: Neuro-Facial Recognition Analysis

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Abstract: Cognitive Trace is a Multimodal Artificial Intelligence system designed to detect cognitive recognition by integrating Electroencephalography (EEG) signals and facial expression analysis. The system primarily focuses on identifying the P300 component in Event-Related Potentials(ERP),which is an involuntary neural response triggered when a subject recognizes familiar stimuli. Alongside this, facial micro-expressions are analysed using a Convolutional Neural Network (CNN) to estimate stress-related emotional states such as fear, anger and surprise.

A weighted probabilistic fusion model combines EEG-based recognition probability and facial stress probability to produce a final confidence score. Unlike traditional lie detection system, the proposed system avoids binary classification and instead provides probabilistic outputs, ensuring ethical and non-invasives. Experimental results indicate that the multimodal approach significantly improves reliability, reduce false positives, and enhance robustness against manipulation.

I. INTRODUCTION

Recognition detection plays a critical role in domains such as criminal investigation, national security, and cognitive neuroscience. Traditional approaches, including polygraph tests, rely on physiological responses like heart rate, respiration, and skin conductivity. However, these methods are often criticized due to their susceptibility to manipulation and inability to directly measure cognitive recognition. To overcome these limitations, this project introduces a multimodal AI framework that combines [1] EEG-based neural signal analysis (P300 detection) [2] Facial expression-based stress analysis.

The P300 signal is well-established neurological marker that appears approximately 300 milliseconds after stimulus presentation indicating recognition. The ERP waveform (your graph) clearly shows this response within the highlighted window (250-500 ms). By integrating brain signals (objective) and facial cues (behavioural),the system provides: High Accuracy, Reduced bias, Ethical decision-making. The proposed system utilizes signal processing techniques to extract ERP features from EEG data and employs Convolutional Neural Network (CNNs) to classify facial emotions. A weighted probabilistic approach ensures a more ethical and scientifically grounded interpretation of results. Furthermore, the system is designed to be non-invasive and user-friendly, incorporating real-time visualization through a dashboard interface. The integration of multimodal data not only improves detection accuracy but also reduces false positives and increases resistance to intentional manipulation. Overall, this work contributes to the field of multimodal artificial intelligence by demonstrating how the fusion od neural and facial data can create a more comprehensive and reliable recognition detection system. The proposed framework has proposed framework has potential applications in forensic investigations, security screening, cognitive neuroscience research, and advanced human-machine interaction systems.

II. RELATED WORK

Recognition detection and deception analysis have been extensively studied using various physiological, behavioural, and computational techniques. Existing approaches can be broadly categorized into traditional physiological methods, EEG-based neural methods, facial expression analysis, and recent multimodal systems.

1) Traditional Physiological-Based Methods: Early recognition and lie detection systems primarily relied on polygraph tests, which measure physiological responses such as Heart rate, Blood pressure, Respiration, Skin conductivity (Galvanic Skin Response-GSR). These methods assume that detective behaviour induces stress, which leads to measurable physiological changes.
2) EEG-Based Recognition Detection: With advancement in neuroscience EEG-based approaches have gained attention for detecting cognitive recognition. P300-Based Detection: The P300 component of Event-Related Potentials (ERP) is widely used for recognition detection: Occurs approximately 300 ms after stimulus, Indicates familiarity or recognition, Involuntary and difficult to manipulate. Researchers such as Farwell and Donchin introduced the concept of “brain fingerprinting”, which used P300 responses to detect concealed information.

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3) Facial Expression Recognition Systems: Facial expression analysis has become prominent with the rise of deep learning. Application: Surveillance system, Emotion-aware AI, Human-computer interaction.
4) Multimodal Recognition Systems: Recent research has focused on combining multiple data sources to improve accuracy.
5) Contribution Of Proposed work: The proposed system addresses these gaps by: Integrating EEG (P300) and facial expression analysis, Using a weighted probabilistic fusion model etc.,. This combination significantly enhances reliability and represents a step forward in multimodal AI-based recognition detection.

III. SYSTEM DESIGN

A. *Architecture Overview*

The architecture of the proposed system, Cognitive Trace: Neuro-Facial Recognition analysis, is designed to integrate neural and behavioural data for accurate recognition detection. The system follows a multiple pipeline architecture , where electroencephalography (EEG) signals and facial expressions are processed in parallel and later combined using a fusion mechanism. The architecture consists of five major layers.

Layer [1]: Input Layer-The input layer collects data from two sources: EEG signals and facial images/video. EEG data captures brain activity in response to stimuli, while a webcam records facial expressions. This layer provides the raw data required for further processing.

Layer [2]: Preprocessing Layer-The preprocessing layer cleans and prepares the raw data for analysis. EEG signals are filtered to remove noise and artifacts, while facial images are resized and normalized. This step improves data quality and ensures accurate feature extraction. Proper preprocessing is essential for reliable system performance.

Layer [3]: Feature Extraction Layer-This layer extracts meaningful information from both EEG and facial data. EEG processing identifies the P300 signals within the 250-500 ms window, indicating recognition. Facial analysis extracts emotion-related features such as stress and fear. These features are used for classification and decision-making.

Layer [4]: Fusion Layer-The fusion layer combines outputs from EEG and facial modules using a weighted approach. EEG is given higher importance, while facial data provides supporting information. This integration improves accuracy and reduces errors. The result is a final recognition probability score.

Layer[5]: Output & Visualization Layer-This layer displays the final results in an understandable format. It shows the ERP waveform, detected emotions, and overall probability score. Visualization tools present the data clearly for users. The system provides probabilistic output instead of binary decisions.

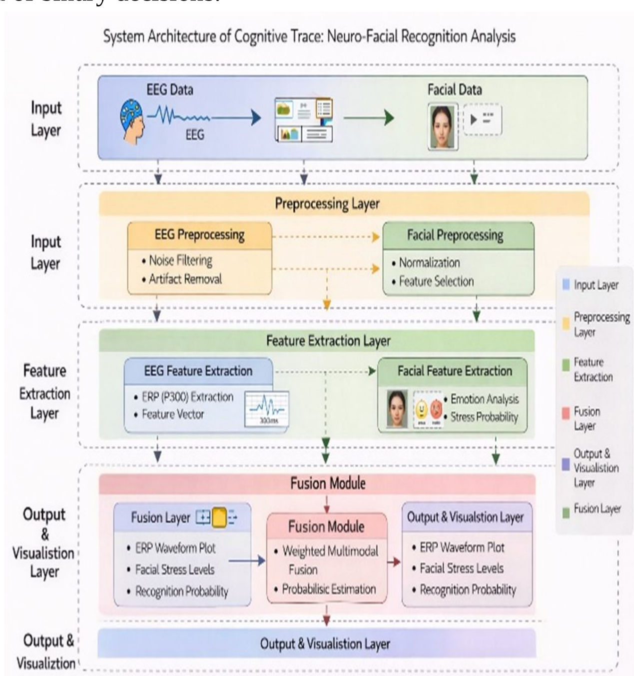

Fig. 1. Cognitive Trace:Neuro-Facial Recognition Analysis System Architecture

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B. Detection Modules

1) Module 1 — EEG Processing Module : The EEG Processing Module is responsible for analysing brain signals to detect cognitive recognition. EEG data is acquired from real-time devices or devices or pre-recorded datasets in .mat format. Since raw EEG signals contain noise and artifacts such as eye blinks and muscle movements, preprocessing techniques including bandpass filtering and artifact removal are applied. This module serves as the primary indicator due to the involuntary nature of brain response.

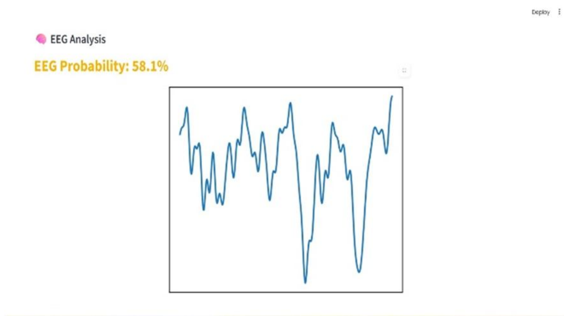

Fig. 2. EEG Process Probability

2) Module 2 — Facial Expression Analysis Module: The Facial Expression Analysis Module processes facial images or video streams to detect emotional states. The input is captured using a webcam or dataset and undergoes preprocessing steps such as face detection, resizing, normalization, and grayscale conversion. A Convolutional Neural Network (CNN) model is used to classify facial expressions into categories such as anger, fear, disgust, and neutral. The output of this module is a stress probability score, which complements the EEG-based recognition analysis.

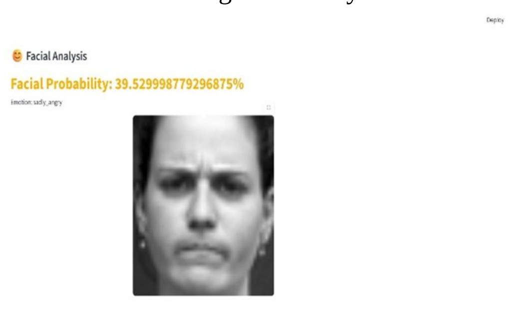

Fig. 3. Facial Expression Analysis Probability

3) Module 3 —Fusion Module: The Fusion Module integrates the output from the EEG Processing Module and the Facial Expression Analysis Module to generate a final decision. The module employs a weighted probabilistic approach, where EEG signals are given higher importance due to their reliability, while facial expressions act as supporting evidence. The fusion process combines the recognition probability obtained from EEG with the stress probability derived from facial analysis to compute a final confidence score. This multimodal integration improves accuracy, reduces false positives, and enhances robustness against manipulation. Instead of producing a binary output, the module provides a probabilistic result, making the sycamore interpretable and ethical.

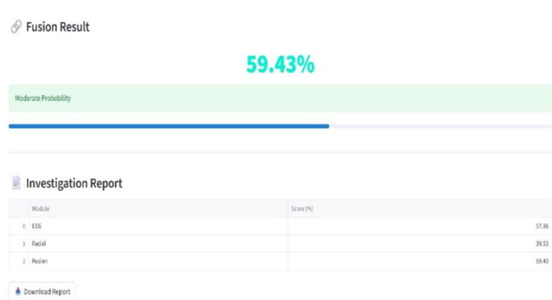

Fig . 4. Fusion module result Moderate Probability.

4) Module 4 — Visualization Module: The visualization Module presents the final results in a clear and user-friendly manner. It displays the ERP waveform highlighting the P300 component, along with detected facial emotions and stress levels. Additionally, the final recognition probability score is shown in percentage form. The module is implemented using interactive tools such as streamlit, enabling real-time visualization and monitoring. By providing graphical and numerical outputs, the system ensures better understanding and analysis of the results. The visualization layer plays a crucial role in making the system practical and user-friendly.

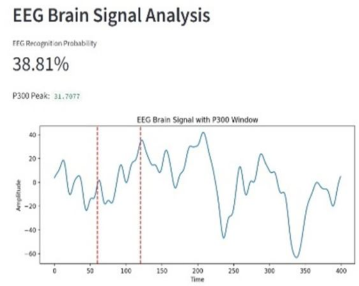

Fig .5.

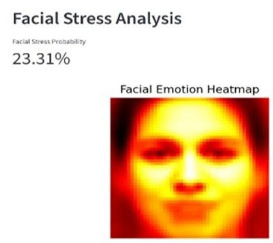

Fig. 6 .

Fig. 7 .

Fig. 8

IV. METHODOLOGY

A. Data Collection

The first stage involves collecting from both neural and behavioural sources.[1]. EEG Data: EEG signals are obtained from publicly available datasets such as BCI datasets in .mat format. These signals capture brain responses when the subject is exposed to specific stimuli. [2]. Facial Data: Facial images or video streams are captured using a webcam or datasets such as CK+.[3]. Stimulus Presentation: Controlled stimuli (images, word, or objects) are show to the subject to trigger cognitive responses, particularly the P300 component. This multimodal data collection ensures the both internal brain activity and external emotional expressions are captured simultaneously.

B. EEG Processing

EEG signals are highly sensitive and often contain noise due to external disturbances and physiological artifacts.[1]. Noise Removal: Bandpass filtering (0.1-30 Hz) is applied to eliminate unwanted frequencies.[2]. Artifacts Removal: Eye blinks, muscle movement, and electrical noise are reduced using preprocessing techniques.[3].Signal Segmentation,[4].. ERP Extraction,[5]. P300 Detection. The amplitude and latency of the P300 wave are used to compute a recognition probability score, making EEG the primary evidence source.

C. Facial Emotion Detection

The facial emotion detection module analyses visual data understand the subject's emotional state.[1]. Face Detection: The system detects and extracts the face region using computer vision techniques.[2]. Preprocessing Images are resized, normalized, and converted to grayscale for consistency.[3]. CNN Model: A Convolutional Neural Network is used to classify facial expressions into categories such as Anger, Fear, Disgust, Neutral etc.,. This module provides insight into behavioural responses that may indicates stress or discomfort during the experiment.

D. Stress probability calculation

The classification emotions are further processed to estimate the stress level of the subject.[1]. Emotions such as anger, fear, and disgust are treated as stress indicators.[2]. Each emotion is assigned a weight based on its intensity.[3]. A stress probability score is calculated to quantify the emotional state. This step adds contextual understanding to the EEG-Based recognition analysis, helping differentiate between normal and stress-induced responses.

E. Multimodal Fusion

The Fusion stage integrates outputs from EEG and facial Modules to produces a final decision.[1]. A weighted probabilistic model is used: EEG contribution:70% (primary evidence), Facial contribution:30% (supporting evidence)[2]. Then fusion process combines: EEG-based recognition probability, Facial-Based stress probability. This multimodal integration:[1]. Reduces false positives,[2]. Improves overall system accuracy.[3]. Enhances robustness against manipulation. Instead of binary outputs, the system generates a continuous confidence score, making it more interpretable and ethical.

F. Result visualization

The final stage presents the output in a clear and user-friendly manner.[1]. ERP Waveform Display: Shows signal patterns with highlighted P300 peak. [2]. Emotion Detection Output: Displays classified facial emotions.[3]. Stress Level Indicator: Shows Calculated stress probability.[4]. Final Recognition Score: Displays overall confidence percentage. The visualization is implemented using interactive tools such as streamlit, enabling real-time monitoring and easy interpretation of results.

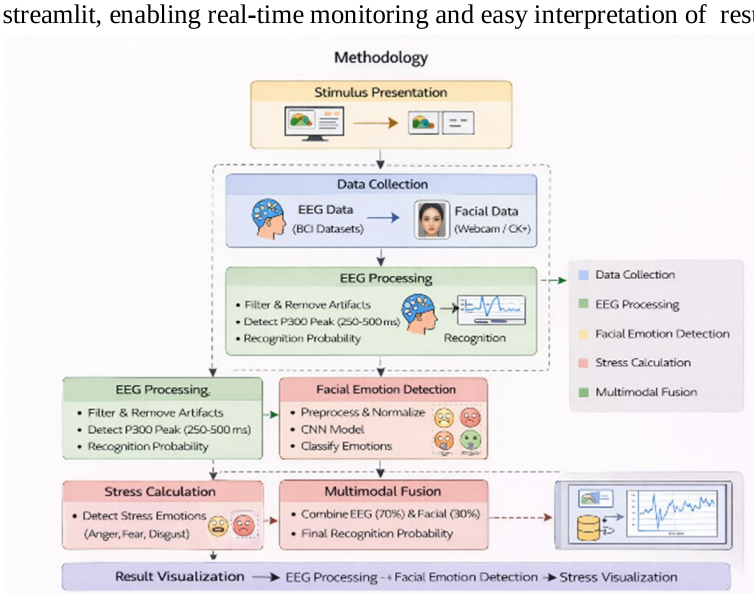

Fig. 9. Methodology using cognitive Trace:Neuro-Facial Recognition Analysis

V. RESULTS AND DISCUSSION

The EEG processing module successfully identified the P300 component within the expected timing window of 250-500 ms. The ERP waveform (as shown in the output graph) clearly highlights a peak around 300 ms, indicating recognition of familiar stimuli. The amplitude and latency of the P300 signal were used to compute recognition probability.

Table 1.FINAL RECOGNITION RESULT CLASSIFICATION TABLE

Recognition percentage(%)	Level	Interpretation
0%-40%	Low	No significant recognition detected
41%-70%	Average	Moderate recognition detected
71%-100%	High	Strong recognition detected

The facial emotion detection module effectively classified emotions such as anger, fear, disgust, and neutral using a CNN model. Based on these classifications, the system calculated a stress probability score, which reflects the emotional states of the subject. The multimodal fusion module combined EEG (70%) and facial (30%) outputs to generate a final recognition confidence score. The results showed that the fusion approach produced more consistent and reliable outputs compared to individual modules.

The results confirm that EEG-based P300 detection is a strong indicator of cognitive recognition. However, EEG signals alone may be affected by noise and individual differences. Facial expression analysis adds contextual information but can be influenced by voluntary control. By combining both modalities, the system overcomes the limitations of individual approaches. The weighted fusion model ensures that EEG signals remain the primary facial data supports decision-making.

Additionally, the use of probabilistic output instead of binary classification enhances the interpretability and ethical applicability of the system. The visualization module further aids in understanding system outputs through graphical representation.

VI. LIMITATIONS AND FUTURE WORK

The proposed system , demonstrates improved performance through multimodal integration, certain limitation, certain limitations still exist. While effective, has certain limitations such as sensitivity of EEG signals to noise and artifacts, and variability in brain responses across different individuals. Facial expression may also be consciously controlled, affecting the reliability of stress detection. Additionally, the system depends on pre-existing the datasets and requires specialized hardware for real-time EEG acquisition. The proposed system can be further enhanced by addressing the above limitations and extending its capabilities.

Future work aims to address these challenges by implementing real-time data processing using live EEG devices and improving accuracy through advanced developing personalized models will also voice and eye tracking. Expanding the dataset and developing personalized model will also improve robustness and real-world applicability.

VII. CONCLUSION

This paper presents a novel multimodal framework for cognitive recognition detection using EEG and facial expression analysis. The system successfully identifies P300 signals and combines them with facial stress indicators to produce a reliable recognition probability. The proposed approach improves accuracy, ensures ethical usage, and reduces dependency on subjective interpretations. Future work can include real-time deployment, larger datasets, and interpretation of additional modalities such as voice and eye tracking.

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