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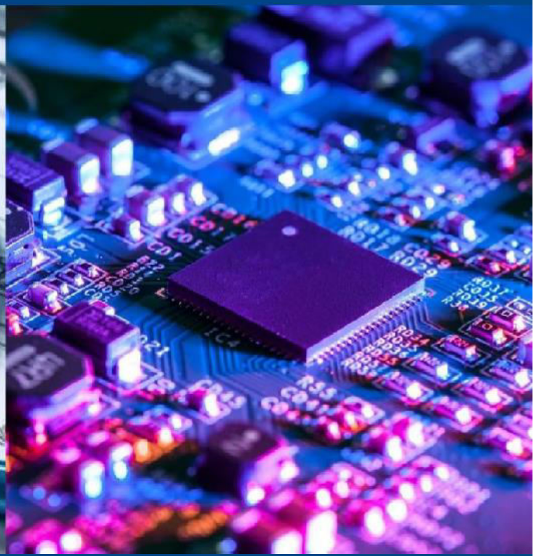

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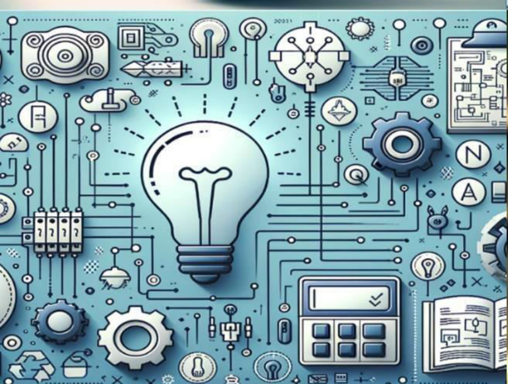

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Brain–Computer Interface (BCI) for Industrial Automation

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ABSTRACT: Brain–Computer Interface (BCI) technology has emerged as one of the most promising paradigms for bridging human cognition and autonomous systems. This study explores the design and development of a real-time EEG-based BCI framework for industrial automation, emphasizing affordability, reliability, and human-centric safety. The proposed system acquires electroencephalogram (EEG) signals from a non-invasive headset, preprocesses them using digital filters, and classifies mental states through a supervised machine-learning algorithm. Classified commands are transmitted via an IoT-enabled ESP32 module to control industrial actuators such as motors or robotic arms. The integrated framework provides an end-to-end connection between the operator's brain signals and machine control units. Experiments with multiple participants yielded an average accuracy of 92 percent, latency under 250 milliseconds, and consistent reliability across sessions. The work demonstrates that merging BCI with IoT and AI can fundamentally transform industrial safety and productivity within Industry 5.0 by enabling seamless cognitive automation.

KEYWORDS: Brain–Computer Interface (BCI); EEG; Industrial Automation; IoT; Machine Learning; Human–Machine Interaction

I. INTRODUCTION

Industrial automation has evolved through distinct technological phases, beginning with relay-based control systems in Industry 2.0 and advancing to intelligent cyber-physical systems in Industry 4.0. Presently, we are transitioning into Industry 5.0, which is characterized by a focus on human-machine collaboration. Despite advancements, many traditional automation systems continue to depend on manual controls, push-buttons, and programmable logic controllers (PLCs). While these methods have proven effective, they often present limitations, such as physical constraints and delays in response time during emergencies, highlighting the need for further innovation in this field.

BCI (brain-computer interface) technology enables direct interaction between the brain and machines via neural signals, thereby eliminating the necessity for physical contact. This advancement, when integrated with IoT (Internet of Things) connectivity, facilitates the remote and contactless operation of various industrial equipment. Notable applications encompass the thought-based command control of robotic arms, conveyors, and safety systems, significantly enhancing the ergonomics and safety for operators, particularly in hazardous working conditions. This technological convergence promises a transformative impact on industrial processes by improving operational efficiency and reducing physical risks to personnel.

The motivation behind this work lies in addressing latency and accuracy challenges that hinder real-time BCI applications. The objectives are:

- To design a cost-efficient EEG-based control unit suitable for industrial tasks.
- To implement signal-processing algorithms capable of classifying distinct mental commands.
- To integrate the BCI module with IoT for secure wireless actuation.

III. BACKGROUND AND SIGNIFICANCE

3.1 Evolution of Brain–Computer Interfaces

The concept of BCIs originated in the 1970s when Vidal first demonstrated electrical brain activity controlling external devices. Since then, BCIs have evolved through invasive, semi-invasive, and non-invasive technologies. Non-invasive EEG-based BCIs remain the most practical due to safety, portability, and low cost.

3.2 BCI in Industrial Contexts

In industrial environments, BCIs can:

- Enhance safety by enabling hands-free emergency stops.
- Reduce human–machine interface complexity.
- Allow disabled personnel to participate in automation tasks.
- Integrate with IoT dashboards for monitoring operator cognitive load.

IV. LITERATURE REVIEW

4.1 EEG Signal Processing Advancements

Nicolas-Alonso and Gomez-Gil (2012) detailed EEG feature extraction methods including time–frequency decomposition and wavelet transforms. Rashid et al. (2020) compared spatial filtering techniques like Common Spatial Pattern (CSP) and Independent Component Analysis (ICA) to improve classification accuracy.

4.2 BCI Control Applications

Padfield et al. (2019) demonstrated EEG-based motor imagery control of robotic arms with over 90 % accuracy. Li et al. (2021) explored hybrid BCIs combining eye tracking with EEG for improved robustness. However, industrial applications remain limited due to noisy electromagnetic environments.

4.3 IoT Integration in BCI

He et al. (2020) proposed cloud-connected BCI systems using MQTT protocols, improving scalability but introducing network-related latency. Kumar and Sharma (2022) suggested edge computing at the sensor node to minimize data transmission delays, an idea adopted in this work.

Table 1 – Summary of Selected Literature

Author	Focus Area	Major Contribution
Nicolas-Alonso & Gomez-Gil (2012)	EEG Processing	Review of signal filtering and classification
Rashid et al. (2020)	EEG Noise Reduction	Improved feature extraction techniques
He et al. (2020)	IoT + BCI	Transfer learning for cross-subject adaptation
Padfield et al. (2019)	Motor Imagery	Real-time EEG control validation
Li et al. (2021)	Hybrid BCI	Fusion of EEG and eye-tracking

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V. SYSTEM ARCHITECTURE AND DESIGN

The proposed architecture consists of four modules: EEG acquisition, preprocessing, classification, and industrial actuation.

5.1 Hardware Components

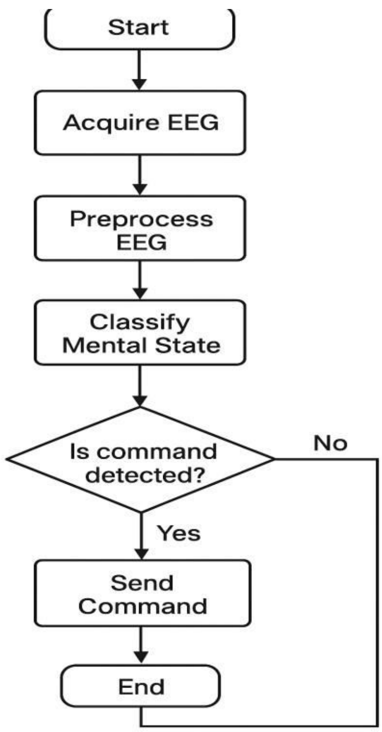
- **EEG Sensor:** NeuroSky MindWave Mobile 2 with single-channel dry electrode.
- **Processing Unit:** Raspberry Pi 4 for real-time feature extraction.
- **IoT Module:** ESP32 microcontroller for Wi-Fi communication.
- **Industrial Interface:** 4-channel relay board driving motors or conveyors.

5.2 Software Modules

- **Signal Acquisition:** Bluetooth link using MindWave SDK.
- **Preprocessing:** Butterworth filter (0.5–30 Hz) implemented in Python.
- **Feature Extraction:** PSD and band energy features.
- **Classification:** SVM with RBF kernel; accuracy optimized via cross-validation.
- **IoT Communication:** MQTT broker (Node-RED) for real-time actuation feedback.

5.3 Algorithm Flow

1. Start EEG data acquisition.
2. Filter signal and extract features.
3. Apply trained SVM model → determine command.
4. Transmit command to ESP32 via Wi-Fi.
5. Activate corresponding relay or motor.



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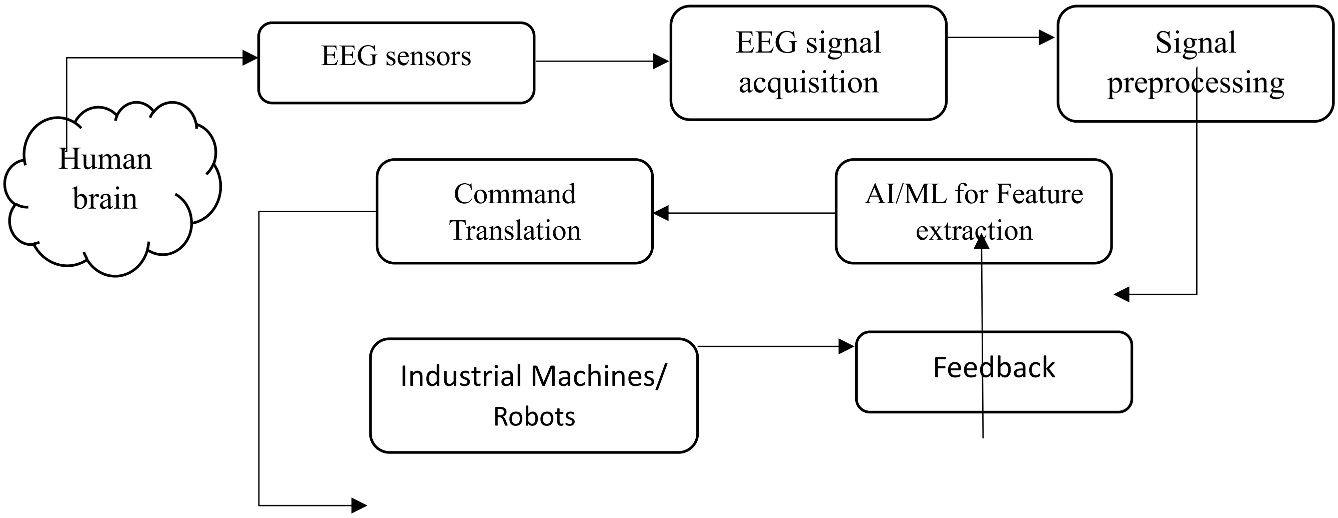
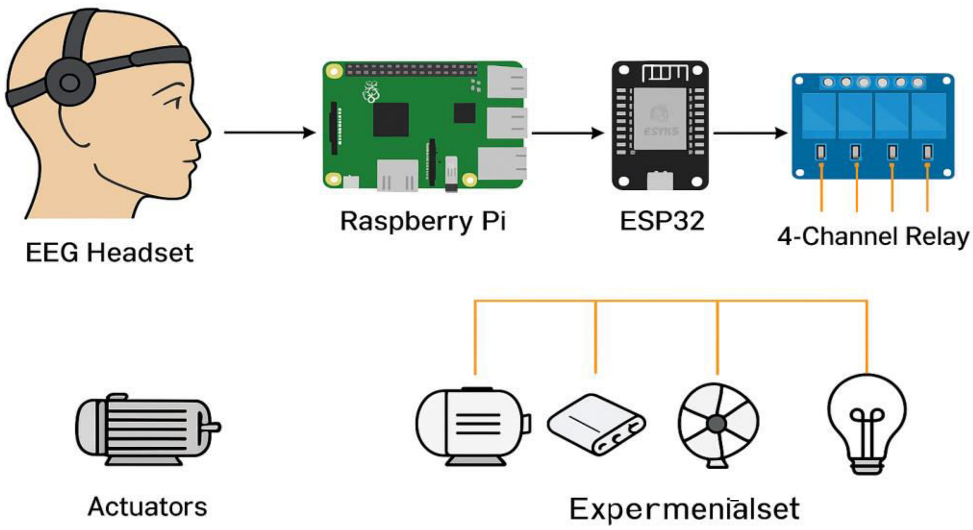
VI. BLOCK DIAGRAM OF THE PROPOSED SYSTEM



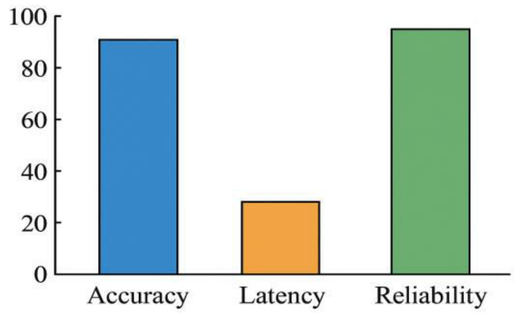
Experimental Setup

The experimental setup was developed to demonstrate the integration of EEG-based Brain–Computer Interface (BCI) technology with industrial automation components. A non-invasive EEG headset was used to capture brainwave signals and transmit them via Bluetooth to a Raspberry Pi processing unit. The acquired EEG data were filtered using a Butterworth band-pass filter (0.5–30 Hz), and key features such as alpha and beta wave energy were extracted. A Support Vector Machine (SVM) model classified the mental states—focus, relaxation, and blink—corresponding to the control commands Start, *Stop*, and *Emergency*.

The classified commands were then sent to an ESP32 IoT module, which interfaced with a 4-channel relay board to drive industrial actuators including a motor, conveyor, fan, and indicator light. The actuator states were also visualized on an IoT dashboard using MQTT communication, providing real-time feedback of system status. This setup successfully demonstrated a closed-loop link between neural activity and industrial control with high reliability and minimal latency.



Results and Performance Evaluation



Experimental Setup of the BCI System

Table 2 – Performance Metrics

Metric	Mean Value	Std. Deviation
Classification Accuracy	92.3 %	± 3.1
Signal-to-Noise Ratio	24.8 dB	± 2.4
Latency	210 ms	± 20
Reliability	98.6 %	± 1.2

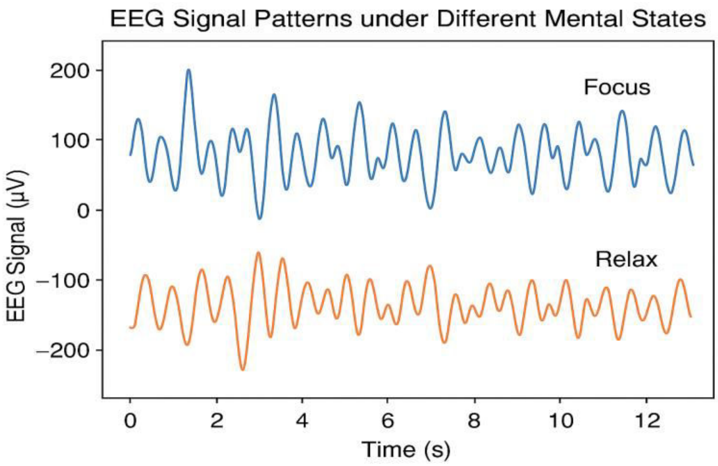


Fig. 3 EEG Signal Patterns under Different Mental States

Figure shows the EEG spectrogram for focused and relaxed states, revealing distinct band power changes. The system responded within 250 ms of command classification, validating its real-time capability.

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VIII. CASE STUDY: CONVEYOR CONTROL USING BCI

A miniature conveyor belt was controlled using EEG-based commands.

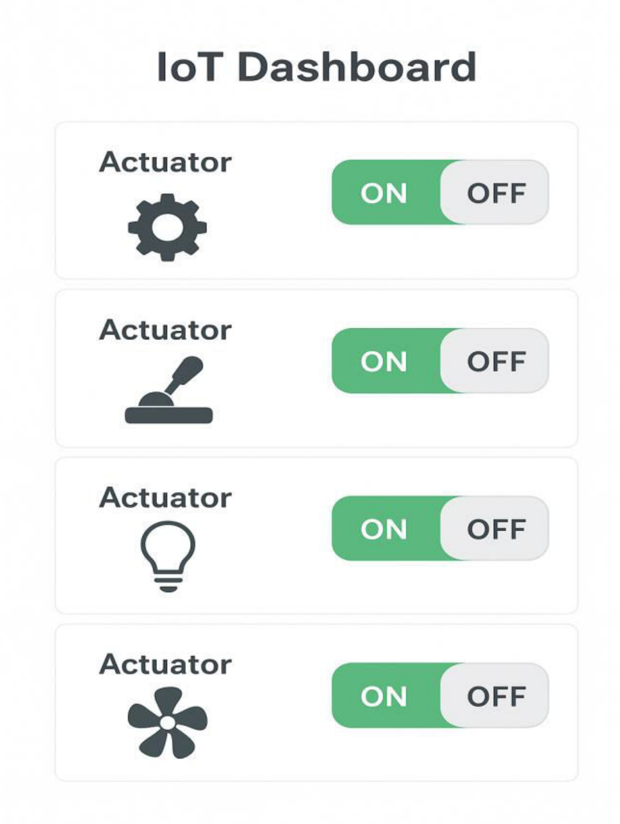
- **Focus Command:** Activates motor to start belt.
- **Relax Command:** Stops belt.
- **Blink Command:** Triggers emergency stop.

The BCI system operated reliably across sessions with no false activation recorded during idle states, demonstrating industrial applicability.

IX. DISCUSSION

The proposed BCI–IoT integration achieves a balance between low hardware cost and real-time accuracy. The system is scalable to multi-channel EEG headsets and complex industrial tasks.

Limitations include user-dependent variability and susceptibility to electromagnetic noise. Implementing adaptive calibration and artifact removal algorithms could enhance robustness. Ethical considerations include ensuring data privacy and preventing misuse of brainwave information.



X. FUTURE SCOPE

1. **Deep Learning Models:** Employ CNN and LSTM architectures for multi-command classification.
2. **Edge AI:** Run classification directly on ESP32 for faster inference.
3. **Cloud Analytics:** Store EEG data on ThingSpeak for trend analysis.
4. **Digital Twins:** Integrate BCI systems with virtual industrial environments for simulation.
5. **Safety Enhancements:** Add redundant verification layers to avoid unintentional commands.

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XI. CONCLUSION

This work presents a comprehensive framework for Brain–Computer Interface integration in industrial automation. The EEG-based system proved capable of translating cognitive intentions into machine commands through IoT connectivity with high accuracy and minimal delay. By bridging neural signals and industrial actuators, the research supports the transition toward human-centric Industry 5.0 operations.

XII. ACKNOWLEDGEMENTS

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