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BioAxis: A Brain Controlled Robotic Arm using EMG Signals and Edge AI

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Abstract: ***The restoration of upper-limb functionality through intelligent assistive systems has become a central focus in biomedical engineering. This study introduces BioAxis, a brain-inspired robotic arm platform that utilizes Electromyography (EMG) signals combined with Edge Artificial Intelligence (Edge AI) for real-time motion control. Unlike conventional brain–computer interface systems that rely solely on EEG, the proposed architecture captures muscle activation patterns from residual limb regions, enabling more stable and intention-driven control.Surface EMG signals are acquired, filtered, segmented, and processed through embedded edge-based machine learning models to classify motor intentions such as grasping, releasing, wrist rotation, and elbow flexion. The integration of Edge AI ensures low latency, improved privacy, and reduced dependency on cloud computing. A multi-degree-of-freedom robotic arm is designed to replicate natural limb kinematics, allowing intuitive interaction.***

I. INTRODUCTION

Loss of upper limb mobility significantly affects independence, occupational participation, and psychological well-being. Advances in neural interfacing and intelligent robotics have enabled the development of systems capable of translating biological signals into mechanical motion.Electromyography (EMG) measures the electrical activity generated by skeletal muscles during contraction. Because EMG signals directly reflect motor neuron activation at the muscular level, they provide a practical and less noise-sensitive alternative to scalp-based neural recordings in certain assistive applications.

In recent years, artificial intelligence has enhanced signal decoding performance. However, many prosthetic systems depend on centralized or cloud-based processing, which increases latency and raises privacy concerns. Edge AI addresses these limitations by performing computation locally on embedded hardware, enabling real-time inference with minimal delay.

The proposed BioAxis system combines EMG-based intention detection with embedded machine learning deployed on edge hardware. The objective is to design a robotic arm capable of responding naturally to muscle activation patterns while maintaining affordability and scalability.

II. LITERATURE REVIEW

Recent research shows significant progress in robotic arm control using EMG and brain signals. EMG-based systems detect muscle activity and convert it into robotic movements using machine learning algorithms. Kim et al. (2023) demonstrated that Edge AI can process EMG signals directly on embedded devices, reducing delay and improving real-time human–robot interaction. Their work highlights the importance of low-latency, on-device AI models.

Satya Sree et al. (2021) and related IEEE studies developed AI-based bionic robotic arms using EMG signals for gesture classification. These systems applied machine learning techniques such as SVM and neural networks to improve movement accuracy. Earlier work by Li et al. (2009) improved EMG gesture recognition accuracy using hybrid classifiers, showing that combining algorithms increases reliability.

Brain–Computer Interface (BCI) research has expanded robotic control using EEG signals. IEEE (2024) presented a robotic arm controlled directly by brain signals. Xu et al. (2022) proposed a hybrid system combining EEG, computer vision, and eye tracking for continuous robotic arm movement. Similarly, studies in 2019 and 2022 introduced hybrid EEG–EMG systems, proving that combining brain and muscle signals enhances accuracy and stability compared to single-signal systems.

Recent advancements such as CognitiveArm (2025) and BIONIX (2025) focused on real-time prosthetic arm control using dual EEG–EMG signals and adaptive machine learning. These systems emphasize affordability, portability, and intelligent signal fusion.

However, many existing systems depend on high-power computing or lack efficient Edge AI integration. Few studies combine hybrid EEG–EMG control with lightweight embedded AI models for real-time processing.

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Therefore, Bioaxis aims to integrate EMG and brain signals with Edge AI to create a low-latency, cost-effective, and intelligent robotic arm system for assistive applications.

III. BACKGROUND

A. *Electromyography (EMG) in Assistive Robotics*

Electromyography records voltage variations produced by muscle fiber depolarization. Surface EMG (sEMG) uses non-invasive electrodes placed on the skin to capture these signals.

EMG signals are characterized by:

- Amplitude range: typically 0–5 mV
- Frequency bandwidth: 20–500 Hz
- Sensitivity to motion artifacts and power-line interference

Because EMG reflects muscular effort rather than abstract neural intention, it often provides clearer command signals for prosthetic control compared to scalp-recorded EEG in voluntary limb movement tasks.

B. *Edge Artificial Intelligence*

Edge AI refers to machine learning inference performed directly on embedded devices such as microcontrollers or single-board computers.

Advantages include:

- Reduced communication latency
- Enhanced data privacy
- Lower bandwidth usage
- Offline functionality

Common edge-compatible models include:

- Lightweight Convolutional Neural Networks (CNN)
- Support Vector Machines (SVM)
- Random Forest classifiers
- Quantized Neural Networks

In assistive robotics, low-latency response is essential to create natural interaction between the user and the prosthetic device.

C. *Robotic Arm Kinematics*

A human arm typically exhibits seven primary degrees of freedom (DOF):

1) Shoulder flexion/extension
2) Shoulder abduction/adduction
3) Shoulder rotation
4) Elbow flexion/extension
5) Forearm pronation/supination
6) Wrist flexion/extension
7) Wrist deviation

Robotic replication of these movements requires coordinated servo actuation and precise torque calculation. Lightweight materials such as PLA composites or aluminum alloys are commonly selected to balance strength and portability.

IV. RELATED WORK

Numerous studies have explored neural and muscular control of robotic manipulators.

A. *EEG-Based Robotic Control*

Research such as Journal of Neural Engineering has documented non-invasive EEG systems for 3D robotic control. These systems primarily rely on motor imagery classification. However, EEG is often affected by low signal-to-noise ratio and environmental interference.

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In IEEE Transactions on Neural Systems and Rehabilitation Engineering, deep learning architectures such as CNN-BiLSTM networks have been applied to EEG datasets for prosthetic arm movement decoding. Although classification accuracy improved, computational demands remained significant.

B. Hybrid EEG–EMG Systems

Studies published in Biomedical Signal Processing and Control investigated combining EEG with EMG to enhance command reliability. Hybrid approaches improve robustness but increase hardware complexity.

C. EMG-Based Prosthetic Arms

EMG-driven prosthetic systems have demonstrated effective gesture recognition using time-domain features such as:

- Root Mean Square (RMS)
- Mean Absolute Value (MAV)
- Zero Crossing Rate (ZCR)
- Waveform Length (WL)

Traditional classification methods such as SVM and KNN achieved moderate accuracy, but real-time adaptation remained a challenge.

D. Edge Computing in Assistive Devices

Recent advancements reported in IEEE Access highlight the feasibility of deploying compact neural networks on embedded processors. These works demonstrate reduced inference time and energy consumption, making edge-based prosthetic systems increasingly viable.

V. RESEARCH GAP

From existing literature, the following limitations are identified:

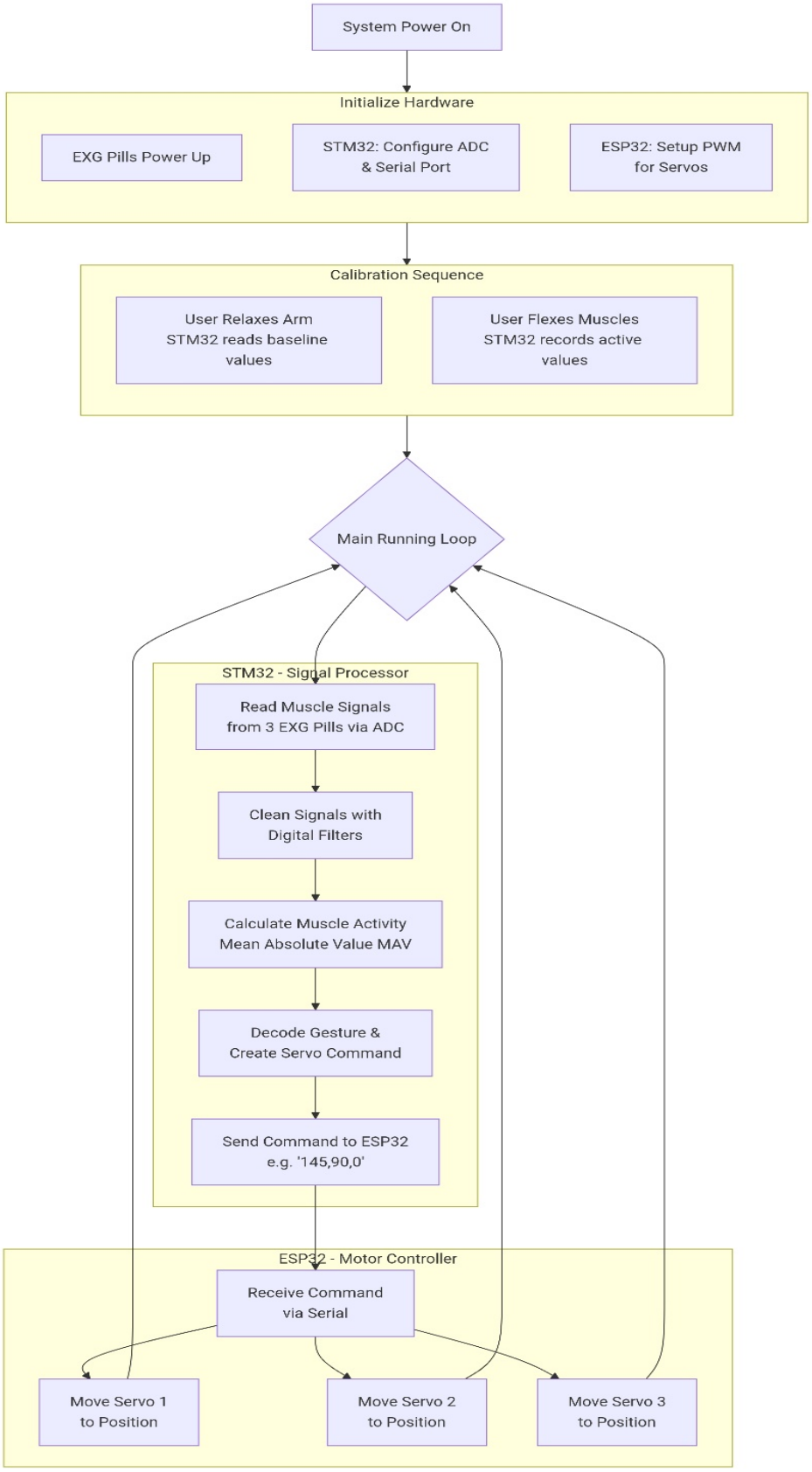
1) Heavy reliance on EEG signals prone to instability
2) Cloud-dependent architectures causing latency
3) Limited personalization for different users
4) High computational requirements unsuitable for portable devices

BioAxis addresses these challenges by:

- Using EMG as the primary control signal
- Deploying optimized machine learning models on edge hardware
- Enabling adaptive training per individual user
- Designing a modular, cost-efficient robotic platform

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VI. FLOWCHART



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VII. PROPOSED SYSTEM OVERVIEW

The BioAxis system consists of four primary modules:

A. Signal Acquisition Unit

The Signal Acquisition Unit is the foundation of the Bioaxis system, responsible for capturing the electrical activity generated by muscles and peripheral nerves.

Key Characteristics:

Electromyography (EMG) Capture: Surface or intramuscular electrodes detect the electrical potentials produced when muscle fibers depolarize. These signal amplitudes are typically in the microvolt to millivolt range and require careful filtering to isolate meaningful patterns.

Real-Time Sampling: Analog signals from multiple electrode sites are sampled at high frequencies (hundreds to thousands of Hz) to preserve the temporal dynamics of muscle activation.

Noise Mitigation: Since biological signals are inherently noisy due to motion artifacts and ambient interference, preprocessing filters (bandpass, notch) are applied to separate relevant EMG components from background noise.

Multi-Channel Integration: A distributed array of sensors provides spatial resolution, enabling the system to distinguish between contraction patterns of different muscle groups.

In summary, this unit reliably transforms weak, raw bioelectrical activity into digitized streams that represent the user's neuromuscular intent.

B. Edge Processing Unit

Once EMG data is digitized, the Edge Processing Unit performs local computation on the device, minimizing latency and reducing dependence on remote servers.

Functions and Benefits:

Local Feature Extraction: Raw signals are processed to derive representative features such as root mean square (RMS), zero crossing rate, waveform length, and frequency domain descriptors. These features serve as inputs to classification models.

Edge Machine Learning: Lightweight neural networks or classifiers (e.g., CNNs, SVMs) run directly on microcontrollers or SoCs equipped with AI acceleration (e.g., Tensor Processing Units). The model interprets muscle activation patterns to infer intended motion categories (e.g., open hand, flex elbow).

Low Latency Response: By performing inference locally, the system minimizes the delay between intention and actuation. This responsiveness is critical for natural and fluid limb control.

Adaptive Calibration: Edge AI modules can recalibrate model weights based on incoming data streams, enabling gradual personalization for individual users without cloud communication.

This unit effectively bridges the raw biological signal to a meaningful interpretation of the user's desired action in real time.

C. Control Mapping Layer

The Control Mapping Layer translates decoded intent into actionable commands that guide the robotic mechanism.

Core Roles:

Interpretation Interpretation: The outputs from the Edge Processing Unit represent abstract action classes or continuous intention vectors. This layer maps those values into specific kinematic targets.

Coordinate Transformation: Intent vectors correspond to joint angles, velocities, or motion trajectories that are transformed into the robot's coordinate frame. Algorithms ensure that the desired motion is compatible with the physical limits of the arm.

Interpolation and Filtering: To avoid abrupt movements, command sequences are smoothed using interpolation or trajectory generation techniques. This ensures stable and safe motion execution.

Safety Checks: Fail-safe constraints (e.g., maximum torque limits, collision avoidance) are embedded here to prevent damage or unintended motion.

By acting as a translator between cognitive intent and mechanical directives, this layer ensures that neural commands are realized in a controlled, safe, and interpretable manner.

D. Robotic Actuation System

The Robotic Actuation System implements the physically executed movements based on high-level commands.

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System Elements:

Actuators: High-precision motors (servo, brushless DC) or artificial muscles provide the torque and motion needed to replicate human limb dynamics. Actuators may be arranged in multiple degrees of freedom to replicate shoulder, elbow, wrist, and finger movements.

Feedback Sensors: Encoders and force sensors within the joints deliver real-time feedback, enabling responsive control and closed-loop stabilization.

Mechanical Structure: Lightweight yet strong materials (aluminum alloys, carbon fiber) form the skeletal framework of the arm. Joint design balances flexibility with load-bearing capability.

Control Firmware: Low-level firmware receives motion targets from the control mapping layer and manages actuation profiles, power distribution, and synchronization across multiple joints.

Together, these components convert coded instructions into accurate, physical movements that reflect the user's intended commands.

VIII. ADVANTAGES

1) Real-Time Response with Low Latency

By performing signal processing and classification directly on an embedded edge device, the system eliminates dependence on cloud communication. This significantly reduces transmission delay and ensures near real-time motor actuation, which is essential for prosthetic and assistive applications.

2) Enhanced Privacy and Data Security

EMG signals contain sensitive physiological information. Processing data locally on the edge device minimizes external data transfer, reducing cybersecurity risks and preserving user confidentiality.

3) Improved Portability and Autonomy

The integration of lightweight microcontrollers and embedded AI frameworks enables compact hardware design. This makes the BioAxis system portable and suitable for wearable or prosthetic implementations without requiring continuous internet connectivity.

4) Energy-Efficient Operation

Edge AI models are optimized for low-power execution. Compared to cloud-based processing, on-device inference consumes less communication energy, making the system more suitable for battery-operated assistive devices.

5) Adaptive Gesture Recognition

Machine learning algorithms allow the system to learn muscle activation patterns specific to each user. This improves gesture recognition accuracy and enables personalized calibration for different muscle strengths and anatomical variations.

6) Reduced Computational Overhead

Feature extraction techniques such as RMS, MAV, waveform length, and zero crossing reduce raw EMG complexity before classification. This makes real-time deployment feasible on constrained embedded platforms.

7) Cost-Effective Implementation

8) Using commercially available EMG sensors and embedded AI development boards reduces overall system cost compared to high-*end neuroprosthetic platforms.*

9) Clinical and Rehabilitation Utility

The system can assist individuals with upper-limb impairments by translating voluntary muscle signals into controlled robotic motion, thereby enhancing independence and quality of life.

IX. FUTURE SCOPE

1) Hybrid EEG-EMG Integration

Future systems may combine EMG with EEG signals to create a multimodal brain–muscle interface. This could improve control accuracy, especially for patients with limited muscle activity.

2) Deep Learning Optimization for Edge Devices

Advances in TinyML and model quantization techniques can enable more complex neural networks to run efficiently on microcontrollers, improving classification precision without increasing hardware demands.

3) Adaptive Self-Learning Systems

Incorporating online learning algorithms would allow the robotic arm to continuously adapt to muscle fatigue, electrode displacement, or long-term physiological changes.

4) Haptic and Sensory Feedback Integration

Adding tactile sensors and force feedback mechanisms could create a bidirectional system where users not only control movement but also perceive touch and grip strength.

5) Cloud-Edge Hybrid Architecture

Although primary processing occurs on the edge, cloud connectivity could be optionally integrated for periodic model updates, remote diagnostics, and long-term performance analytics.

X. CONCLUSION

BioAxis proposes a novel integration of EMG-based intention decoding and Edge AI-driven robotic control. By shifting computation to embedded platforms and focusing on muscular signals for direct motion interpretation, the system enhances responsiveness, portability, and affordability.

This approach demonstrates strong potential for next-generation prosthetic and rehabilitation technologies, particularly in resource-limited settings.

REFERENCES

[1] E. Kim, J. Shin, Y. Kwon, and B. Park, "EMG-Based Dynamic Hand Gesture Recognition Using Edge AI for Human–Robot Interaction," Electronics, vol. 12, no. 7, Art. no. 1541, Mar. 2023, doi: 10.3390/electronics12071541.

[2] K. P. N. V. Satya Sree, T. Bikku, S. Mounika, N. Ravinder, M. Lakshmana Kumar, and C. Prasad, "EMG Controlled Bionic Robotic Arm using Artificial Intelligence and Machine Learning," in Proc. 2021 Fifth Int. Conf. I-SMAC (IoT in Social, Mobile, Analytics and Cloud), Amaravati, India, 2021, doi: 10.1109/I-SMAC52383.2021.9640623.

[3] "EMG Controlled Bionic Robotic Arm using Artificial Intelligence and Machine Learning," SciSpace PDF, 2020.

[4] H. F. Hassan, S. J. Abou-Loukh, and I. K. Ibraheem, "Teleoperated Robotic Arm Movement Using EMG Signal With Wearable MYO Armband," arXiv, Oct. 2018.

[5] "Implementation of a Brain-Computer Interface for Robotic Arm Control," IEEE Xplore, 2024.

[6] "EMG Controlled Bionic Robotic Arm using Artificial Intelligence and Machine Learning — Amrita Vishwa Vidyapeetham," IEEE Xplore, 2021.

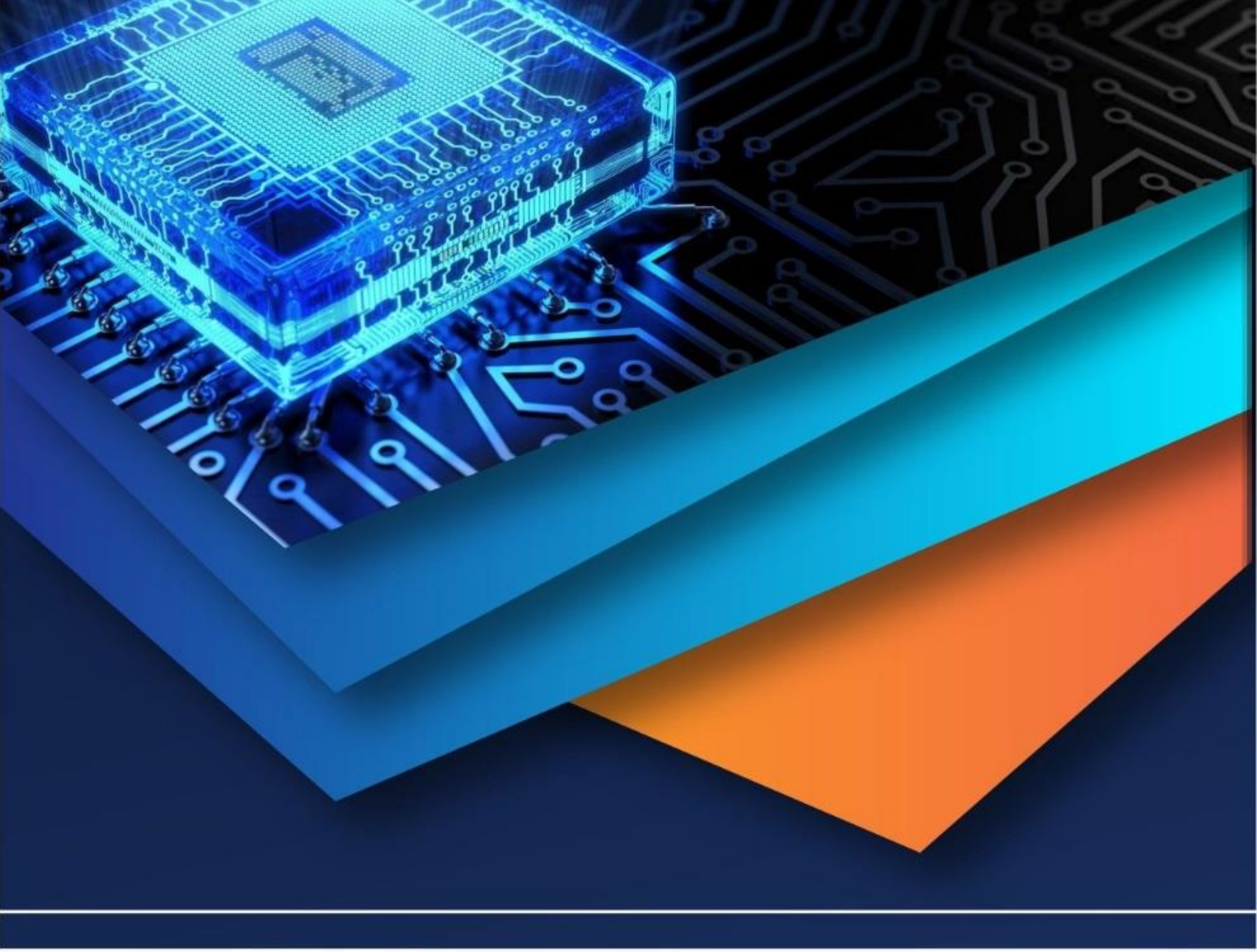
[7] R. Li, S.-W. Ye, and Z.-Z. Shi, "SVM-KNN Classifier — A New Method of Improving Accuracy for EMG Gesture Recognition," in Proc. IEEE Int. Conf. Comput. Sci. & Inf. Technology, Aug. 2009.

[8] E. Xu, W. Li, D. Liu, K. Zhang, M. Miao, G. Xu, and A. Song, "Continuous Hybrid BCI Control for Robotic Arm Using Noninvasive EEG, Computer Vision, and Eye Tracking," Mathematics, vol. 10, no. 4, pp. 618, Feb. 2022, doi: 10.3390/math10040618.

[9] "Robotic arm control system based on brain-muscle mixed signals," Elsevier Biomed. Signal Process. & Control, vol. 77, Aug. 2022, doi: 10.1016/j.bspc.2022.103754.

[10] "Hybrid EEG-EMG Based Brain Computer Interface (BCI) System for Real-Time Robotic Arm Control," Am. J. Mod. Lett. Eng. Tech. Sci., 2019, doi: 10.5185/amlett.2019.2171.

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