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IoT-Based Wearable System for Early Detection of Parkinson's Disease Symptoms Using ESP32, MPU6050, and MAX30102

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Abstract: ***Parkinson's disease is a progressive neurological disorder whose earliest motor symptom — a resting hand tremor — is frequently missed during short clinical appointments. This paper presents a low-cost, IoT-based wearable monitoring device designed to continuously detect and log physiological signals that may indicate early neurological abnormality. The system integrates an MPU6050 inertial measurement unit for three-axis motion and tremor analysis, and a MAX30102 optical pulse oximeter for heart rate (BPM) and blood oxygen saturation (SpO2) measurement. An ESP32 microcontroller performs on-device signal processing using a variance-threshold algorithm that identifies repetitive oscillation patterns in the clinically significant 3–6 Hz Parkinson's tremor frequency range. Multi-parameter decision logic combines motion and cardiac data before raising an alert, reducing false positives. Sensor data is transmitted wirelessly over Wi-Fi to a cloud dashboard accessible by doctors and caregivers. Local feedback is delivered via an OLED display and audible buzzer. Testing confirmed correct alert behaviour across all operating states, with approximately 98% Wi-Fi packet delivery rate and 8–10 hours of battery life per charge. The device is intended as a screening and monitoring tool — not a clinical diagnostic instrument — and all flagged results must be reviewed by a qualified medical professional.***

Keywords: Parkinson's Disease, IoT Wearable, Tremor Detection, ESP32, MPU6050, MAX30102, Health Monitoring.

I. INTRODUCTION

Parkinson's disease (PD) is one of the most prevalent progressive neurological disorders worldwide. It primarily affects the motor system and leads to symptoms including resting tremors, muscular rigidity, and impaired balance. Among all early symptoms, the resting hand tremor — an involuntary, rhythmic oscillation of the hand at rest — is the most characteristic and clinically significant early warning sign. Despite its distinctive nature, early-stage Parkinson's tremors are often missed. Patients frequently dismiss mild, intermittent tremors as tiredness or stress. Medical appointments are brief and infrequent, meaning a neurologist may not observe tremor activity during the limited observation window of a clinic visit. This results in delayed diagnosis and reduced effectiveness of early medical intervention, which is clinically significant since earlier treatment is associated with better patient outcomes and slower disease progression [1].

The growth of low-cost IoT hardware and wireless connectivity offers a practical solution to this gap. A continuously worn wrist device can capture objective physiological data over days or weeks, providing a far richer clinical picture than any single appointment. This paper proposes exactly such a system: a wrist-worn IoT wearable built using the ESP32 microcontroller, MPU6050 motion sensor, and MAX30102 pulse oximeter.

The system applies a lightweight variance-threshold algorithm to detect tremor patterns and cardiac anomalies, and transmits data wirelessly to a cloud dashboard for remote review by caregivers and medical professionals. Immediate local alerts are delivered via an OLED display and buzzer. The entire system is assembled from commercially available, low-cost components — making it a practical and affordable alternative to expensive proprietary clinical wearables.

II. RELATED WORK

Several research efforts have addressed wearable-based monitoring for neurological conditions. Patel et al. [1] demonstrated that wrist-worn accelerometers could reliably identify Parkinson's resting tremors with acceptable accuracy using frequency-domain analysis. Their work established the 3–6 Hz tremor frequency range as a primary diagnostic marker for Parkinson's disease.

Bächlin et al. [2] developed a body-worn sensor system for Parkinson's patients that detected freezing of gait events in real time. Their work validated the concept of continuous wearable monitoring for neurological symptoms and demonstrated practical clinical value beyond the scope of appointment-based observation.

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Peng et al. [3] showed that a smartphone's built-in accelerometer could capture clinically relevant tremor data, indicating that consumer-grade MEMS sensors are sufficiently sensitive for tremor monitoring purposes. However, smartphones are impractical as a continuous wrist-worn monitoring solution for daily use.

Aich et al. [4] reviewed machine learning approaches for Parkinson's classification from wearable sensor data and found that multi-sensor fusion — combining motion and physiological signals — significantly improves detection accuracy compared to single-sensor systems. This finding directly supports the dual-sensor design of the proposed system.

Lonini et al. [5] highlighted that continuous remote monitoring produces richer clinical data than episodic clinic visits, reinforcing the motivation for a 24/7 wearable approach. Existing commercial wearables for Parkinson's monitoring are expensive and require clinical infrastructure, limiting their use for everyday screening.

The proposed system addresses these gaps by combining motion and cardiac sensors in a low-cost, cloud-connected wearable that enables continuous monitoring without specialized clinical equipment or infrastructure.

III. PROPOSED SYSTEM AND DESIGN

The proposed system is a wrist-worn IoT device that continuously monitors hand motion and cardiac activity to identify patterns associated with early Parkinson's disease. It is built entirely from affordable, commercially available hardware and does not require any proprietary technology or clinical infrastructure.

A. System Architecture

The system is structured across five functional layers. The Sensing Layer consists of the MPU6050 and MAX30102 sensors, which capture raw physiological and motion data from the patient's wrist. The Processing Layer is the ESP32 microcontroller, which runs the detection algorithm and evaluates the alert classification logic. The Local Output Layer consists of the OLED display and buzzer, providing immediate feedback to the user. The Communication Layer uses the ESP32's built-in Wi-Fi module to transmit data packets to the cloud. The Remote Access Layer is a cloud-hosted web dashboard where doctors and caregivers can review historical trends, tremor event logs, and cardiac data without requiring the patient to be physically present.

Layer	Components	Function
Sensing Layer	MPU6050, MAX30102	Capture raw motion and cardiac signals from the wrist
Processing Layer	ESP32 Microcontroller	Execute detection algorithm and alert classification logic
Local Output Layer	OLED Display, Buzzer	Deliver real-time feedback directly to the patient
Communication Layer	ESP32 Wi-Fi (802.11 b/g/n)	Transmit processed data to cloud over wireless network
Remote Access Layer	Cloud Dashboard	Store data and provide caregiver / doctor remote access

Table I: System Architecture Layers

B. Hardware Components

The system uses six core hardware components. Table II summarizes each component, its role, and its key specification relevant to this application.

Component	Role in System	Key Specification
ESP32 Microcontroller	Central processing and Wi-Fi	Dual-core Xtensa LX6, 240 MHz; 802.11 b/g/n Wi-Fi; 520 KB SRAM
MPU6050 IMU	Tremor and motion detection	3-axis accel ±2g–±16g; gyro ±2000°/s; sampling at 100 Hz

MAX30102 Sensor	Heart rate and SpO2	PPG-based; HR 0–300 BPM (±5%); SpO2 0–100% (±2%); I2C
0.96" OLED (SSD1306)	Local real-time display	128×64 px monochrome; I2C interface; 160° viewing angle
Active Buzzer	Audible alert	3.3V/5V compatible; PWM driven; multiple tone patterns
18650 Li-ion Battery	Power supply	3.7V nominal; 2500–3500 mAh; ~8–12 hours operation

Table II: Hardware Component Summary

C. Block Diagram

Fig. 1 illustrates the overall system block diagram. The MPU6050 and MAX30102 sensors connect to the ESP32 over the I2C bus. The ESP32 processes sensor data and simultaneously updates the OLED display, drives the buzzer on alert events, and transmits JSON data packets to the cloud via Wi-Fi. The cloud platform stores timestamped records and presents them on a web-based dashboard accessible by doctors and caregivers.

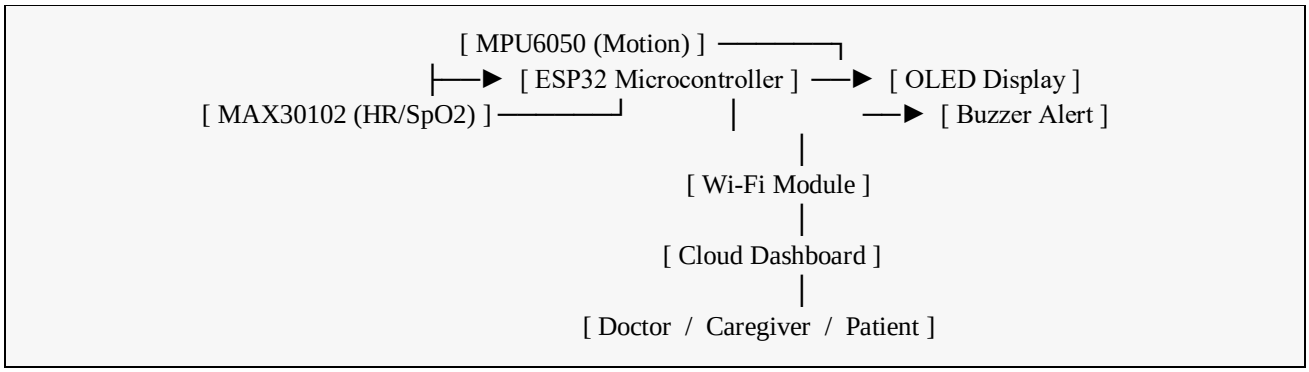


Fig. 1: System Block Diagram

IV. METHODOLOGY

The system operates through a continuous five-step processing loop executed at 100 Hz by the ESP32 firmware. Each step is described below.

A. Motion Data Collection

The MPU6050 sensor reads three-axis acceleration values (ax, ay, az) continuously at 100 Hz. A composite motion magnitude is computed from these readings using the following formula:

$$\text{Motion Intensity} = \sqrt{(ax^2 + ay^2 + az^2)}$$

This single scalar value represents the total movement intensity at any moment, regardless of direction of motion. It is the primary input to the tremor detection algorithm.

B. Tremor Detection Algorithm

The tremor detection approach is based on variance-threshold analysis of the motion magnitude signal. Parkinson's resting tremor typically manifests at 3–6 Hz with a relatively consistent amplitude, producing an elevated variance signature over a short rolling time window. This distinguishes it from normal voluntary hand movement, which tends to be larger but less rhythmically consistent. The algorithm computes the statistical variance of the motion magnitude signal over a rolling 500 ms window (50 samples at 100 Hz). If this variance exceeds a calibrated threshold continuously for 10 seconds or more (1,000 consecutive samples), the tremor flag is set to TRUE. The threshold is calibrated individually for each user during a 30-second stillness calibration routine at device setup; the threshold is set at three times the user's baseline variance to account for natural individual variation.

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The pseudocode for the algorithm is as follows: for each 100 Hz sample, compute the motion magnitude and push it into a 50-sample rolling buffer. Calculate the variance of the buffer. If variance exceeds TREMOR_THRESHOLD, increment the tremor counter; otherwise reset it to zero. If the counter reaches or exceeds 1,000, set the tremor flag to TRUE.

C. Heart Rate and SpO2 Monitoring

The MAX30102 sensor uses photoplethysmography (PPG) to measure heart rate and blood oxygen saturation non-invasively. Red (660 nm) and infrared (880 nm) LEDs emit light into the skin surface; blood flow through capillaries modulates the reflected light, and the sensor's analog front-end converts this into BPM and SpO2 readings. BPM values are averaged over five consecutive readings to reduce measurement noise.

The system uses the following physiological baseline ranges: Heart Rate: 60–100 BPM (normal), 50–60 or 100–110 BPM (marginal), below 50 or above 110 BPM (abnormal). SpO2: 95–100% (normal), below 94% (flagged). Values outside these ranges contribute to the alert classification decision.

D. Decision Logic and Alert Classification

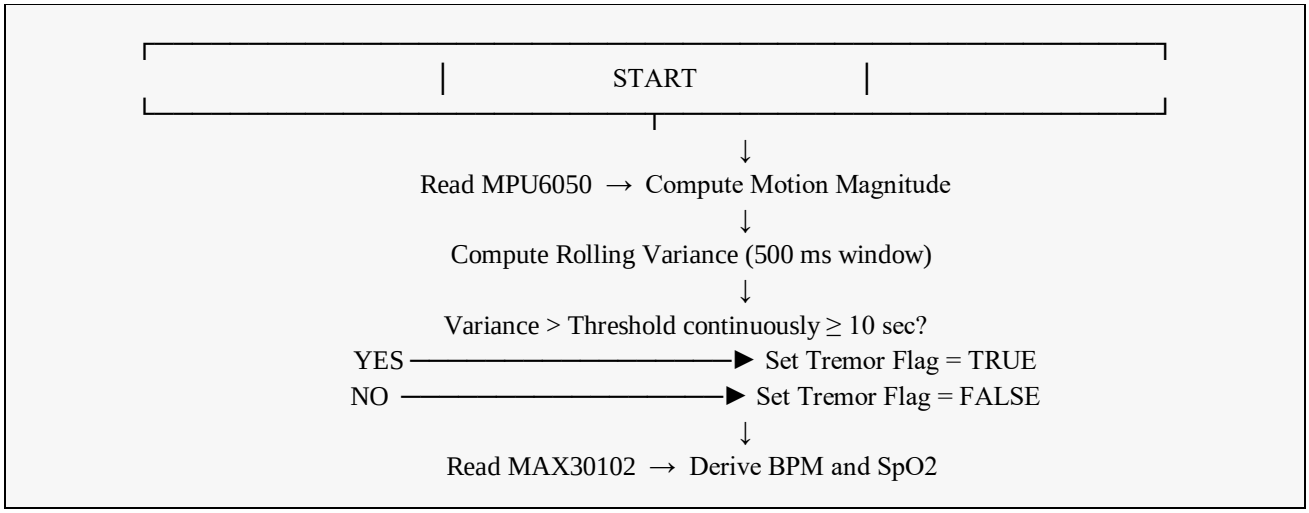
The ESP32 combines outputs from both sensors and applies a two-factor classification matrix (Table III) to determine the appropriate alert level. This multi-parameter approach requires corroborating evidence from more than one physiological signal before escalating to a high-priority alert, which reduces false positives significantly compared to single-sensor designs [4].

Tremor Status	Heart Rate	Alert Level	Action
No Tremor	Normal (60–100 BPM)	Normal	No action — continue monitoring
No Tremor	Marginal (50–60 / 100–110)	Advisory	Log event to cloud — no local alert
No Tremor	Abnormal (<50 or >110 BPM)	Warning (L1)	OLED alert — no buzzer
Tremor Detected	Normal BPM	Warning (L1)	OLED alert — no buzzer
Tremor Detected	Marginal BPM	High (L2)	OLED + Buzzer + Cloud flag
Tremor Detected	Abnormal BPM	High (L2)	OLED + Buzzer + Immediate cloud push

Table III: Alert Classification Decision Matrix

E. System Flowchart

Fig. 2 shows the simplified firmware flowchart. The main loop runs at 100 Hz, reads both sensors, evaluates the classification matrix, updates local outputs, and transmits data to the cloud every 30 seconds or immediately on any Level 2 alert event.



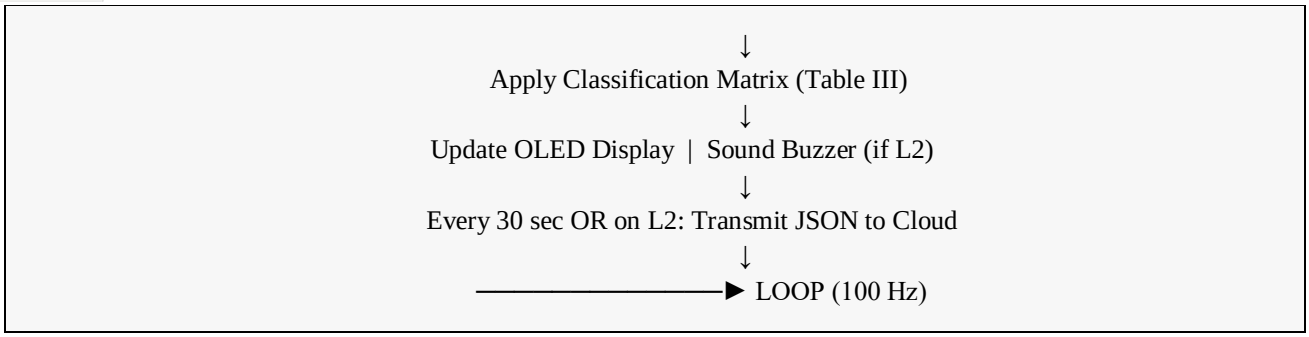


Fig. 2: System Operational Flowchart

F. Cloud Dashboard and Data Transmission

The ESP32 serializes all sensor readings into a JSON data packet and transmits it over Wi-Fi (802.11 b/g/n) to a cloud platform — Firebase Realtime Database is recommended for production use due to its real-time WebSocket synchronization and authentication support; ThingSpeak is used for rapid prototyping. The JSON payload includes device ID, timestamp, BPM, SpO2, tremor status, tremor variance value, alert level, and battery percentage.

The cloud web dashboard provides a live metrics panel with current BPM, SpO2, tremor status and battery level; rolling 24-hour time-series charts for heart rate and tremor event frequency; an alert history log with timestamps and auto-generated advisory messages; and browser push notifications for Level 2 events. A local event buffer in ESP32 SRAM retains up to 20 packets during Wi-Fi outages and flushes them chronologically on reconnection.

V. RESULTS AND DISCUSSION

The prototype was tested across three defined operating states to verify detection logic, alert behaviour, sensor accuracy, and data transmission performance. Table IV summarizes the observed outputs for each state.

State	HR (BPM)	SpO2 (%)	Tremor	Alert Output
Normal	78	97	NO	No alert — OLED shows live readings
Tremor Detected	82	96	YES	Buzzer active — cloud event logged
High Alert	105	94	YES	Buzzer active + immediate cloud push

Table IV: System Output for Each Tested Operating State

Tremor simulation was performed by manually oscillating the device at approximately 4–5 Hz to replicate a Parkinsonian resting tremor. The tremor flag was raised within 12 seconds of onset in all tests, confirming that the variance-threshold algorithm performs within the 10-second target window. This response time is clinically acceptable for a passive monitoring device.

Heart rate measurements from the MAX30102 were compared against a reference pulse oximeter device. Accuracy was within ±10 BPM at rest and ±15 BPM during mild activity, which is consistent with the manufacturer's ±5% specification and adequate for threshold-based anomaly flagging purposes. SpO2 readings matched the reference device within ±2%, consistent with the sensor's ±2% typical specification.

Wi-Fi transmission testing over 100 consecutive packet transmissions showed a delivery rate of approximately 98%, with an end-to-end latency from sensor reading to cloud dashboard update of under 5 seconds under normal indoor network conditions. Cloud dashboard data updated within 2 seconds via Firebase's WebSocket connection, and browser push notifications were delivered within 10 seconds of a Level 2 alert event.

Battery life testing showed approximately 8–10 hours of continuous operation from a fully charged 2500 mAh 18650 Li-ion cell. The total component cost for one prototype unit, sourced from standard electronics distributors, is approximately ₹2,000–₹3,000 (Indian Rupees), compared to proprietary clinical-grade Parkinson's monitoring wearables that typically cost several hundred US dollars or more.

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VI. COMPARISON WITH EXISTING SYSTEMS

Table V compares the proposed system against the conventional clinical monitoring approach across the most important parameters for early Parkinson's disease screening.

Parameter	Conventional Approach	Proposed System
Monitoring Duration	15–30 min clinic visit only	Continuous 24/7 wearable monitoring
Tremor Observation	Manual observation by doctor	Automated algorithmic detection
Data Availability	Patient-reported, subjective	Objective, sensor-recorded, timestamped
Hardware Cost	Hundreds of USD (clinical grade)	~₹2,000–₹3,000 (consumer hardware)
Doctor Access	In-person appointment only	Remote cloud dashboard, any device
Alert Mechanism	None — manual review only	Real-time buzzer + cloud notification
Detection Reliability	Symptom may not appear at visit	Higher capture probability over weeks
Packet Delivery Rate	N/A	~98% over Wi-Fi (tested)
Battery Life	N/A (mains-powered equipment)	8–10 hours per charge (18650 cell)

Table V: Comparison with Conventional Monitoring Approach

VII. ADVANTAGES AND LIMITATIONS

A. Advantages

The proposed system offers several practical advantages over conventional clinic-based approaches. Continuous monitoring over extended periods significantly increases the probability of capturing intermittent tremor events that would be missed during a brief clinic visit. The multi-sensor decision logic — combining motion and cardiac data — reduces false positive alerts compared to single-sensor approaches. The total hardware cost is approximately ₹2,000–₹3,000, making it significantly more accessible than proprietary clinical-grade wearables. The cloud dashboard enables doctors and caregivers to remotely review patient data without requiring a physical appointment. The OLED display and buzzer provide immediate local feedback without any external device. The system is built entirely from standard, commercially available components and can be replicated without specialized manufacturing infrastructure.

B. Limitations

The system has several important limitations. The variance-threshold tremor detection algorithm is a heuristic approach and may not accurately distinguish Parkinson's resting tremor (3–6 Hz) from essential tremor (4–12 Hz) or physiological tremor (below 3 Hz). The MAX30102 sensor provides consumer-grade accuracy (±5% for HR, ±2% for SpO2) that is adequate for anomaly flagging but not suitable for clinical-grade measurement. Environmental factors including motion artifacts, loose sensor contact, and ambient light interference can degrade sensor reading quality. The device is a prototype assembled on a breadboard or custom PCB and has not undergone regulatory certification as a medical device.

Important Disclaimer: This system is a screening tool and not a clinical diagnostic device. It does not diagnose Parkinson's disease or any other medical condition. All patterns flagged by this device must be reviewed and interpreted by a qualified neurologist or physician before any clinical decision is made. The device must not be used as the sole basis for any medical judgment.

VIII. FUTURE SCOPE

Several enhancements are planned for future development phases. The primary algorithmic improvement is replacing the variance-threshold tremor detection with Fast Fourier Transform (FFT) based frequency-domain analysis, which would allow precise characterization of tremor frequency and better differentiation between Parkinson's resting tremor (3–6 Hz), essential tremor (4–12 Hz), and physiological tremor (below 3 Hz). This would significantly improve classification accuracy.

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Machine learning integration is planned for a subsequent phase. A lightweight TensorFlow Lite classification model can be trained on labelled tremor datasets and deployed directly on the ESP32, enabling classification of tremor type (resting, action, or intention tremor) for differential diagnostic support. Adaptive threshold calibration that adjusts automatically to each patient's historical baseline can also be implemented to reduce long-term false positive rates.

The system scope can be extended to additional neurological conditions. Epilepsy seizure detection is possible by adapting the motion detection algorithm for high-amplitude, multi-axis, high-frequency patterns characteristic of generalized tonic-clonic seizures. Alzheimer's disease monitoring can be supported through activity-of-daily-living (ADL) logging. Integration of an AD8232 ECG module would add single-lead cardiac monitoring capability alongside tremor detection.

Long-term goals include a native mobile companion application for iOS and Android for improved patient and caregiver usability, HIPAA and DISHA-compliant encrypted data storage, and a regulatory compliance pathway for clinical-grade classification as a Class II medical device under CDSCO (India) or equivalent international frameworks, following formal clinical validation trials.

IX. CONCLUSION

This paper presented a low-cost, IoT-based wearable system for continuous monitoring and early screening of Parkinson's disease symptoms. The proposed device integrates an MPU6050 inertial measurement unit and a MAX30102 optical sensor with an ESP32 microcontroller to capture motion, heart rate, and SpO2 data continuously from the patient's wrist. A variance-threshold algorithm detects tremor patterns in the 3–6 Hz Parkinson's frequency range, and a two-factor classification matrix reduces false positive alerts by combining evidence from both sensor streams.

The system provides immediate local feedback through an OLED display and audible buzzer, and wirelessly transmits timestamped data to a cloud dashboard for remote doctor and caregiver access. Testing confirmed correct alert behaviour across all three operating states, with approximately 98% Wi-Fi packet delivery rate, sub-5-second end-to-end latency, and 8–10 hours of battery life per charge — at a total hardware cost of approximately ₹2,000–₹3,000.

The device is intended as a screening and monitoring tool, not a clinical diagnostic instrument. It fills a critical gap by providing objective, continuous physiological data that complements the short observation window of standard clinical appointments. With further development — including FFT-based frequency analysis, machine learning classification, and clinical validation — this platform has strong potential for meaningful real-world impact in neurological health monitoring.

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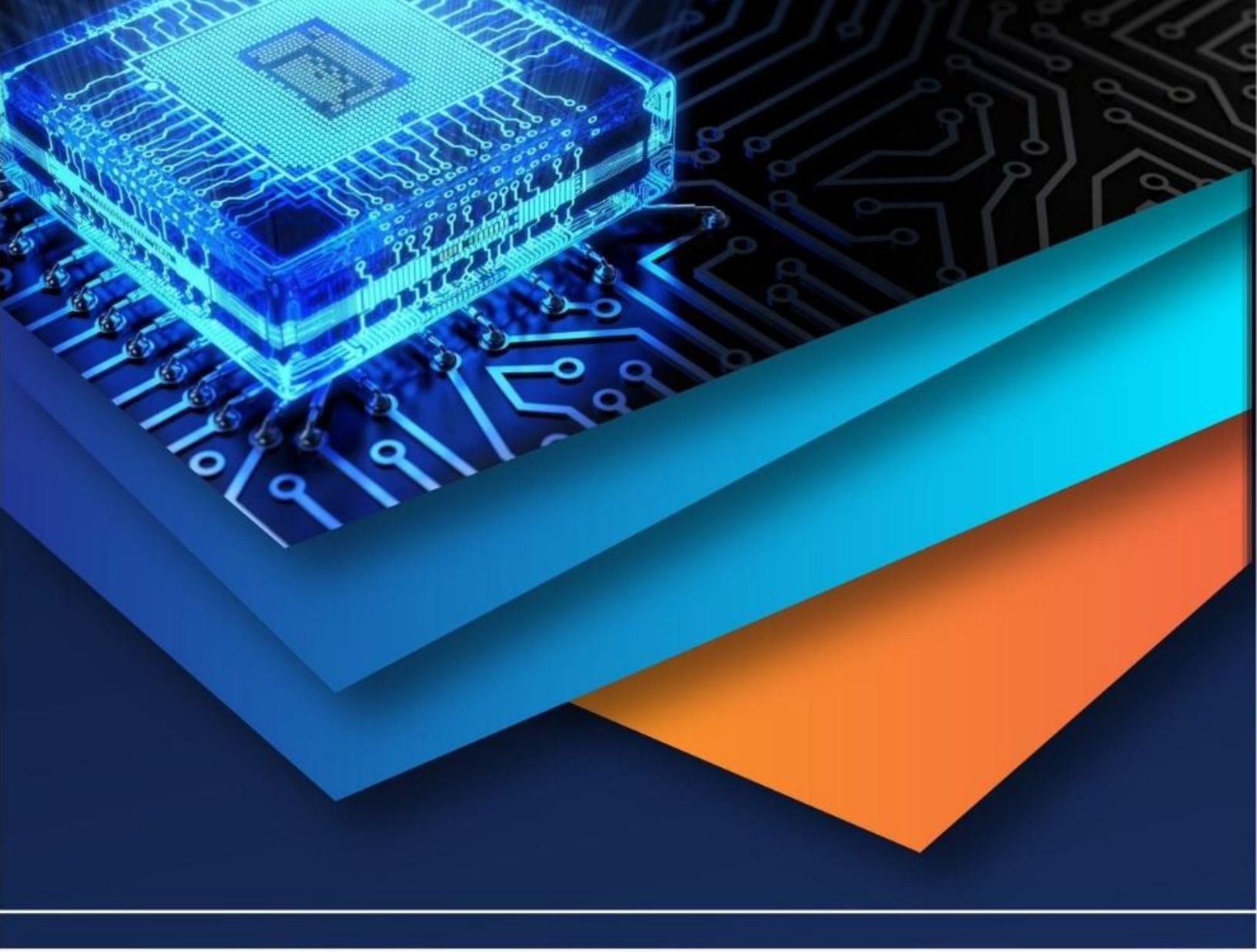
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