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CARES: Cognitive Assistance and Response Emergency System for Visually Impaired Individuals

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Abstract: ***CARES (Cognitive Assistance and Response Emergency System) is an assistive prototype designed to support visually impaired individuals during emergencies using ESP32, MAX30102, NEO-6M GPS, Python backend, SQLite and a web dashboard. It analyses heart-rate variations against personal baselines using deviation, trends, persistence and recovery to classify LOW, MEDIUM or HIGH risk and trigger guardian SMS alerts. Preliminary software testing and simulated evaluation demonstrate its functionality; however, hardware readings remain intermittent, continuous monitoring is not established, and clinical validation is pending.***

Keywords: ***Assistive technology, visually impaired users, Internet of Things, ESP32, MAX30102, GPS tracking, personal baseline, physiological risk assessment, guardian notification, emergency assistance.***

I. INTRODUCTION

Visually impaired individuals rely on assistive technologies for mobility and information access. However, navigation assistance alone may not address situations where a person feels unwell or requires timely support. Wearable sensors, low-cost microcontrollers and wireless communication connect physiological observations with remote assistance systems. CARES (Cognitive Assistance and Response Emergency System) is a prototype integrating an ESP32 controller, MAX30102 optical pulse sensor and NEO-6M GPS module with a Python backend, database and browser-based dashboard. It collects heart-rate observations and location coordinates, evaluates readings against a personal baseline and presents explainable LOW, MEDIUM or HIGH risk states.

The decision engine uses temporal features, confidence assessment and persistence checks to reduce reactions to isolated fluctuations. Based on risk levels, guardian-related actions are initiated through the notification layer. The system distinguishes generated actions, provider-accepted requests and confirmed message delivery for notification transparency. CARES integrates physiological monitoring, location context, explainable risk assessment and staged guardian communication into one workflow. This study presents its architecture, implementation and preliminary evaluation through software tests, simulated data and demonstration observations. CARES is not a medical diagnostic system, does not infer cognitive or emotional states, and does not replace professional medical care or emergency services.

II. LITERATURE SURVEY

Wearable physiological monitoring provides a foundation for observing signals associated with changes in a user's condition. Cano et al. [1] review wearable physiological-signal solutions for stress monitoring in individuals with autism spectrum disorder, while Pinge et al. [2] survey wearable sensors and methods used for stress detection and monitoring. Vos et al. [4] discuss the generalisation challenges of machine-learning approaches for stress monitoring from wearable devices. Gjoreski et al. [5] investigate continuous stress detection using a wrist-worn device in laboratory and real-life settings. Sunny et al. [11] review anomaly-detection frameworks for wearable data, highlighting approaches for identifying unusual patterns in physiological measurements. These studies demonstrate the relevance of wearable signals, anomaly detection and personalised interpretation, although their focus is primarily on stress assessment and physiological monitoring rather than guardian escalation for visually impaired users.

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IoT-based health-monitoring studies illustrate how sensor readings can be collected and communicated through connected devices. Nath et al. [6] describe an IoT smart health-monitoring approach using wearable sensors, while Karthik et al. [7] focus on real-time monitoring and alerting using ESP32. Lee et al. [8] address AI-driven wearable cognitive monitoring and emergency response. Arpaia et al. [12] present a wearable system for remote vital-sign monitoring that uses deep learning and personalised anomaly detection to identify unusual physiological patterns and generate alerts. These studies are relevant to CARES because they demonstrate the integration of sensing, embedded communication, personalised analysis, remote monitoring and notification mechanisms. However, the available studies do not establish the same combination of persistence-gated risk assessment and notification-status safeguards implemented in CARES.

Assistive technologies for visually impaired people commonly emphasise navigation, obstacle awareness and scene understanding. Baig et al. [3] present an AI-based wearable vision-assistance system, and Lokesh et al. [9] describe an IoT-powered wearable assist device for visually impaired users. Okolo et al. [10] review challenges and opportunities in navigation assistance for visually impaired persons. Such work primarily addresses mobility and environmental perception, whereas CARES explores an additional support layer based on physiological observations and guardian communication.

Research Gap: The selected literature covers wearable physiological monitoring, stress analysis, anomaly detection, IoT health systems and navigation assistance. CARES combines these themes in a prototype workflow that evaluates heart-rate observations against a personal baseline and maps persistent risk states to explainable guardian-related actions using GPS context. Its contribution is architectural and exploratory; real-world effectiveness and clinical validity remain to be established.

TABLE II.1. COMPARISON OF REVIEWED WORK WITH CARES

Ref.	Approach	Technologies / focus	Contribution represented by the cited work	Gap relative to CARES
[1]	Wearable physiological monitoring in ASD	Wearable physiological signals	Systematic review of stress-monitoring solutions	Stress monitoring focus; not the CARES guardian workflow
[2]	Stress detection using wearables	Wearable sensors and detection methods	Systematic review of detection and monitoring approaches	Does not establish baseline-relative emergency escalation for visually impaired users
[3]	AI wearable vision assistance	Wearable vision / AI	Vision-based assistance for visually impaired users	Perception focus rather than physiological risk assessment
[4]	Generalizable wearable stress monitoring	Machine learning and wearable data	Review of generalisation challenges	Stress classification focus; not guardian notification
[5]	Continuous stress detection	Wrist-worn device	Laboratory and real-life continuous detection study	Does not address staged guardian escalation
[6]	IoT smart health monitoring	Wearable sensors and IoT	Connected health-monitoring approach	The supplied citation does not establish CARES-specific decision safeguards
[7]	ESP32 real-time health monitoring	ESP32 and alert system	Real-time monitoring and alerting focus	Personal-baseline and persistence details not established by supplied citation
[8]	AI wearable cognitive monitoring	Wearable AI and emergency response	Combines monitoring and emergency-response theme	Different target and risk model; not shown to provide CARES workflow
[9]	IoT wearable assistive device	Wearable IoT assistive technology	Assistive support for visually impaired users	Need for physiological baseline and explicit action-status handling remains
[10]	Navigation assistance review	Assistive navigation systems	Summarises challenges and opportunities	Navigation emphasis rather than physiological monitoring and guardian escalation
[11]	Wearable-data anomaly detection review	Wearable sensors and anomaly-detection algorithms	Reviews methods for identifying unusual wearable physiological data	Does not describe an integrated GPS and guardian-escalation workflow
[12]	Personalised vital-sign monitoring	Wearable transducer and LSTM Autoencoder	Enables personalised anomaly detection and remote vital-sign monitoring	Focuses on patient telemonitoring rather than visually impaired users and staged guardian actions

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III. PROPOSED METHODOLOGY AND DISCUSSION

A. System Overview

As shown in Fig. 1, the MAX30102 supplies optical pulse observations to the ESP32 DevKit V1 through I²C, while the NEO-6M GPS receiver provides location data through a serial interface. The ESP32 uses Wi-Fi to send structured HTTP requests to the Python backend. The backend validates device and user information, stores events in SQLite and passes valid physiological samples to the risk-assessment engine. The engine compares readings with a personal baseline, derives temporal features and produces an explainable LOW, MEDIUM or HIGH state. The guardian-action layer maps the state to configured actions, while the browser dashboard receives live updates through server-sent events (SSE). SMS behaviour depends on provider configuration; generated, mock, pending, sent and delivered statuses are not interchangeable.

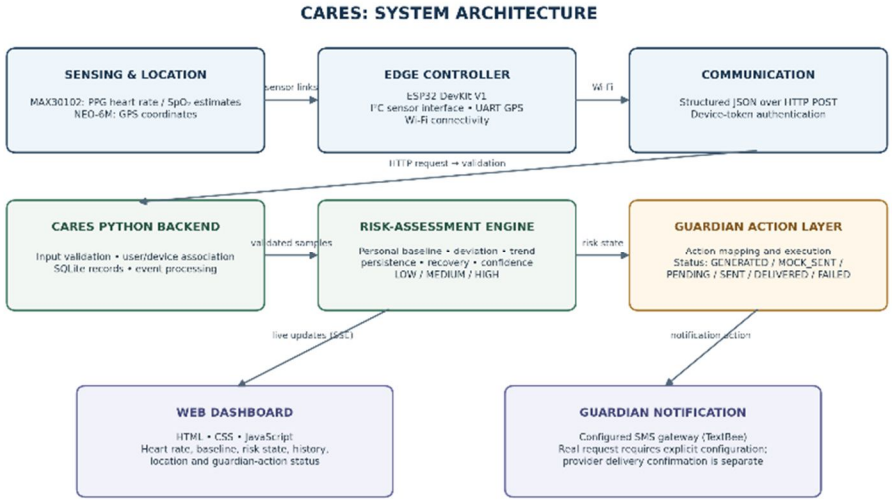


Fig. III.1. System architecture of the CARES prototype

B. Hardware

Table II.1 lists the twelve items reported by the team as used in the prototype. The MAX30102 is an optical module with red and infrared LEDs and a photodetector, read over I²C [11]. The NEO-6M is a u-blox 6 GPS receiver [12]. Pin assignments are defined in the device firmware and are not reproduced in this paper because the firmware was not available for review. The prototype is powered over USB during bench tests. No battery, charging circuit or enclosure is specified, so the assembly in Fig. 2 should be regarded as a bench prototype and not as a validated wearable device.

TABLE III.1. HARDWARE ITEMS REPORTED AS USED IN THE PROTOTYPE

No.	Item	Role
1	ESP32 DevKit V1	Microcontroller; sensor interface and Wi-Fi
2	MAX30102 sensor module	Optical PPG pulse sensing (I²C)
3	NEO-6M GPS module	Location source (UART)
4	Breadboard	Temporary assembly during prototyping
5	Male-to-male jumper wires	Breadboard interconnections
6	Male-to-female jumper wires	Module-to-board connections
7	Female-to-female jumper wires	Connections between module header pins
8	Perfboard	Semi-permanent circuit assembly
9	Header pins	Module and board connection points
10	USB data cable	Programming, serial diagnostics and power
11	Flexible 4-wire cable	Flexible interconnection

C. Backend interfaces and security

Table III.1 lists the main routes. Browser requests are authenticated with a session cookie. Passwords are stored with PBKDF2-HMAC-SHA256 (600,000 iterations), session tokens are stored only as SHA-256 hashes and expire after 24 hours, and data are queried per user. Two device routes use the shared device token. The ingest route accepts a GPS location with a timestamp and, optionally, a heart-rate and oxygen-saturation pair. A GPS-only payload never runs the decision engine or sends a message. When a heart-rate pair is present it is validated, timestamped with the device time if that is close to the server time (and with the server clock otherwise), labelled as a hardware sample and passed to the decision engine. A separate telemetry route, added later, stores a heart-rate value and location for display only. By design it never invokes the engine, creates incidents or sends messages, and automated tests check this separation. The separation prevents an unvalidated, intermittent sensor stream from triggering escalation.

D. Personal baseline

The engine does not use a fixed population limit. For each user it learns a reference heart rate. Initial calibration requires at least 300 seconds of trusted, low-risk observations. After calibration the reference adapts slowly (an exponential update factor of 0.01) and only when the current state is LOW, the observation is valid and the deviation is within 10 bpm, so that abnormal readings are not absorbed into the reference. The dashboard reports calibration progress as trusted samples out of a 30-sample window together with the 300-second minimum, and returns a calibrating output with a fixed confidence of 0.2 until the baseline is ready.

E. Risk score and candidate level

The risk score is calculated using three bounded terms: deviation score , percentage deviation score and rate-of-change score, as defined in Eqs. (1) - (3). The deviation score (S_{dev})is calculated based on the absolute heart-rate deviation (ΔHR), as shown in Eq. (1). The percentage deviation score represents the relative heart-rate change, as given in Eq. (2). The rate-of-change score considers the heart-rate variation in beats per minute per second, as expressed in Eq. (3). These three scores are combined to calculate the final risk score (S_{pct}), which is limited to a maximum of 100, as shown in Eq. (4).

$$S_{dev} = \min(50, 50 \cdot \Delta HR / 25) \quad (1)$$

$$S_{pct} = \min(30, 30 \cdot \Delta\% / 32) \quad (2)$$

$$S_{rate} = \min(20, \max(0, 20 \cdot r / 1.2)) \quad (3)$$

$$S = \min(100, S_{dev} + S_{pct} + S_{rate}) \quad (4)$$

A candidate level is classified as HIGH when $\Delta HR \geq 25$bpm, $\Delta\% \geq 32$ or $\Delta HR \geq 40$bpm (extreme spike). MEDIUM is assigned when $\Delta HR \geq 12.5$ bpm, $\Delta\% \geq 16.5$, or $r \geq 1.2$ bpm/s. Otherwise, the candidate level is LOW. These values are default engineering configuration settings and are not clinically validated limits.

F. Evidence confidence and escalation

Evidence confidence is $C = \min(1, 0.7 \cdot \min(1, n/30) + P + 0.1)$, where n is the number of retained baseline samples and $P = \min(0.3, 0.1 \cdot k)$ when the abnormality has persisted for $k > 1$ samples, and $P = 0$ otherwise. A candidate level is not applied immediately. The state machine moves from LOW to MEDIUM after three consecutive persistent samples, and from MEDIUM to HIGH after five persistent samples with $C \geq 0.6$. An extreme spike can reach HIGH after two consecutive extreme samples with the same confidence condition. De-escalation requires five consecutive lower candidate levels. The persistence rule is intended to prevent isolated transient readings from raising an alert, at the cost of a delay of several samples. Each output carries reason codes and a text explanation, for example BASELINE_CALIBRATING or STABLE_BASELINE.

G. Guardian actions and notification safeguards

SMS is sent through TextBee [13], an open-source gateway that uses an Android phone as the sender. The default provider is a mock. A real message is requested only when the provider is set to TextBee, the demonstration option CARES_DEMO_REAL_SMS is enabled in the server configuration, and the user ticks a real-SMS option when starting the demonstration. In tests, repeated HIGH readings within one episode produce a single SMS request. A location is attached to a guardian message only if it is recent (at most 300 seconds old) and belongs to the same user; otherwise the message states that no GPS fix is available.

IV. RESULTS AND DISCUSSION

A. System Implementation and Hardware Demonstration

The implemented CARES system demonstrates its major functionalities through the interface and hardware prototype. **Fig. 4.1** shows the sign-in page, providing access to the system, while **Fig. 4.2** illustrates the hardware components and their interfacing connections, including the ESP32, heart rate sensor and GPS module. **Fig. 4.3** displays the location page after receiving GPS data from the hardware device. **Fig. 4.4** demonstrates the SMS notification received by the guardian's phone through the TextBee API during a simulated high-risk heart rate scenario.

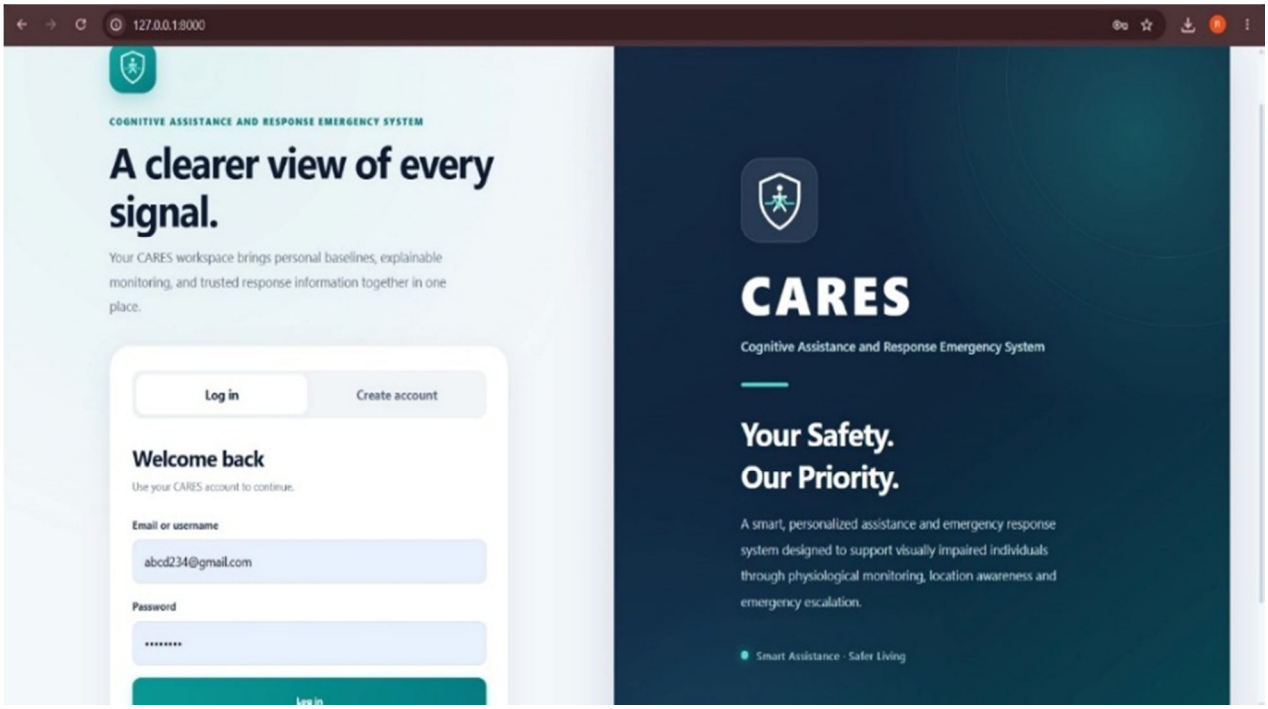


Fig. 4.1 CARES Sign-in page

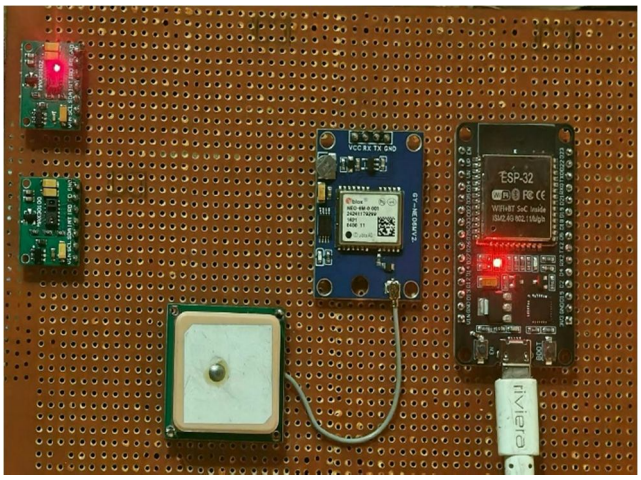


Fig.4.2 Hardware components and interfacing of the proposed system.

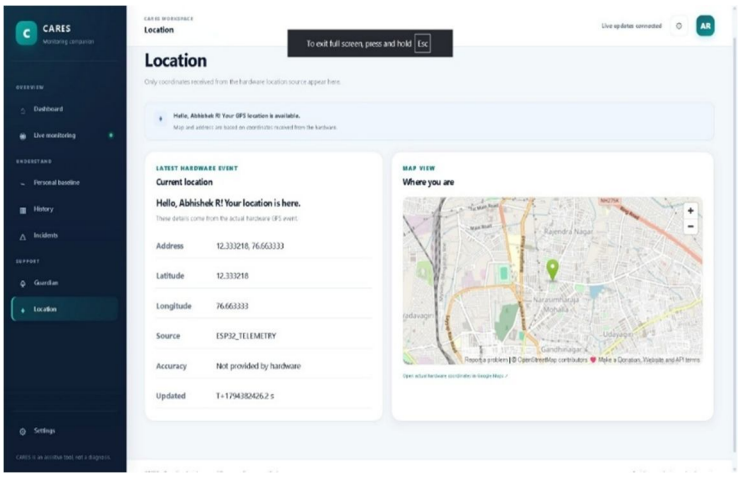


Fig.4.3 shows the location page after a hardware GPS connections location was received

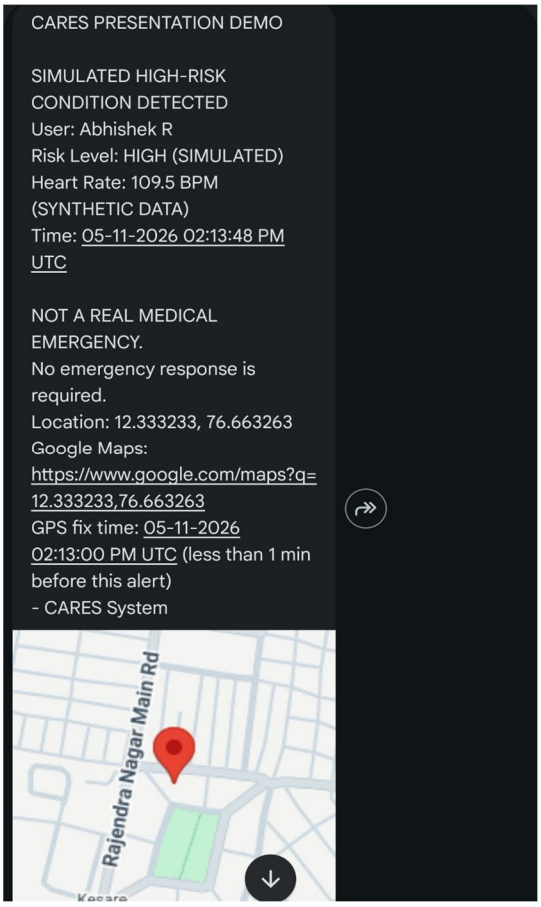


Fig.4.4 Real-time SMS alert sent to the guardian based on elevated heart rate detected by the hardware system.

B. Limitations

The main limitations are as follows. Heart-rate readings from the MAX30102 were intermittent and continuous monitoring was not achieved; the low-cost prototype has no battery, enclosure or validated mounting. The data source of the dashboard heart-rate values rests on the team's report. Risk thresholds are engineering defaults and have not been validated against real recordings or reference instruments. The simulated evaluation uses scripted streams, one seed and no confidence intervals, so it does not show detection performance on people. The demonstration SMS was synthetic and sent to a team-controlled phone; a provider delivery receipt, a guardian's response and real emergency use were not tested. GPS availability depends on reception, and only one fix was observed. No usability study with visually impaired participants, clinical validation or security assessment has been carried out, and one automated front-end test fails in the evaluated snapshot.

V. CONCLUSION AND FUTURE SCOPE

CARES presents a prototype framework that connects wearable physiological sensing and GPS-based location information with embedded communication, backend processing, explainable risk assessment and guardian-related actions for visually impaired individuals. The ESP32 integrates the MAX30102 and NEO-6M modules and transmits available observations to a Python backend, where validated heart-rate samples are assessed relative to a personal baseline. The decision engine considers deviation, trend, persistence, recovery and evidence confidence before producing LOW, MEDIUM or HIGH states. These states are displayed through a browser dashboard and mapped to monitoring or notification actions. The software evaluation included 173 automated tests, with 172 passing in the reported snapshot, and a simulated-cohort comparison in which CARES reduced state oscillations while introducing trade-offs in latency and false-positive rate. A synthetic demonstration exercised the guardian workflow and produced one SMS on a team-controlled phone. Nevertheless, sensor readings were intermittent, continuous monitoring was not established, and the prototype has not been clinically validated. CARES should therefore be regarded as an exploratory assistive system rather than a diagnostic or emergency service.

A. Future Scope

(1) Improve sensor reliability and continuous monitoring through better MAX30102 contact, signal-quality assessment, longer timestamped hardware-to-backend tests and validation against reference instruments. (2) Strengthen real-world readiness by validating risk thresholds with representative data, verifying provider-confirmed guardian delivery and location freshness, improving accessible dashboard usability and conducting controlled user studies with appropriate ethical and safety oversight.

VI. ACKNOWLEDGEMENT

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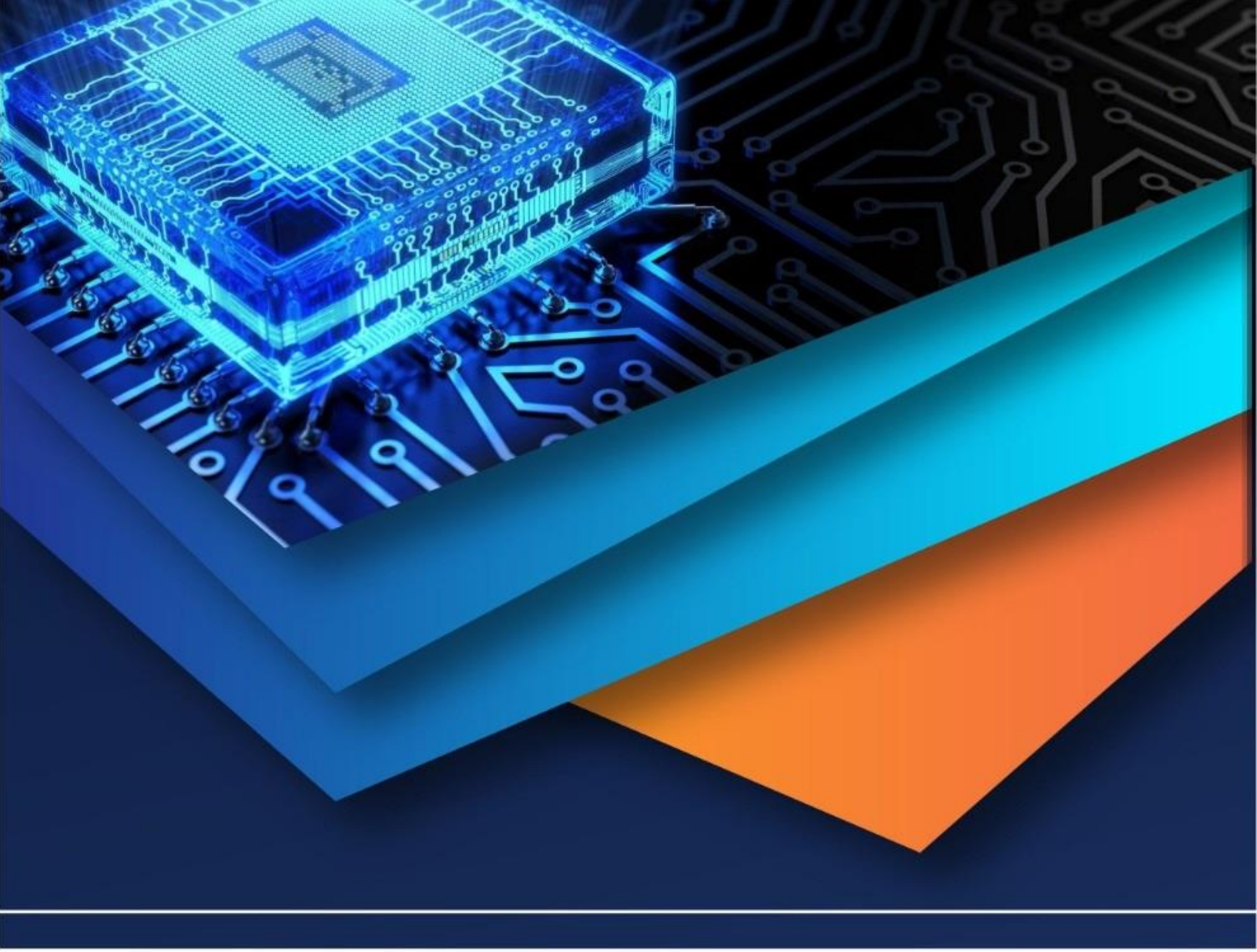
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