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A Real-Time IoT-Based System for Early Warning of Physiological Deterioration in Post-Operative Patients

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***Abstract**: The patients in the post-operative state are always at risk of sudden physiological state deterioration. This paper proposes a health monitoring system through periodic short-term physiological data acquisition using an ESP32-based system with ECG and SpO2 sensors. Multimodal vital signals are collected during structured monitoring sessions and sent to a central server for real-time visualization and trend analysis through a web interface. The proposed health monitoring system uses temporal trend analysis with clinical threshold reasoning. This approach helps in the graded assessment of patient state through medically defined parameter ranges rather than binary reasoning. This reduces the chances of false alarms and increases the reliability of the monitoring system. The results show stable system performance with reliable communication and anomaly detection. The proposed approach will be useful in cost-effective deployment of the system.*
***Keywords**: Internet of Things (IoT), Post-Operative Monitoring, ECG Monitoring, SpO_2 Monitoring, Edge-Based Health Systems, Preventive Healthcare, Clinical Thresholding*

I. INTRODUCTION

The integration of IoT technologies into health systems has made it possible to continuously monitor patients' physiological parameters through connected devices. IoT-based health monitoring systems are extensively researched for continuous health monitoring of patients by tracking vital signs such as heart rate, blood oxygen saturation (SpO_2), and electrocardiogram (ECG) signals [10], [20]. IoT-based health monitoring systems use embedded platforms and wireless communication to transmit patients' data to cloud-based infrastructures for increased accessibility [6], [7].

Several existing systems are based on continuous health monitoring systems that use wearable sensors and cloud-based infrastructures. IoT-based health monitoring systems that use ESP32-based platforms and cloud-based infrastructures are used for the real-time transmission of patients' data for remote health applications [7]. AI-based systems are also extensively researched for health monitoring systems by integrating data analysis techniques for increased health knowledge [8]. Similarly, cloud-based health monitoring systems are also researched for health monitoring applications by providing increased data storage and analysis capabilities for remote health management and increased health knowledge [6]. However, these systems are mostly based on continuous health monitoring systems that use threshold-based systems for health monitoring. Such systems are associated with increased data redundancy, power consumption, and false alarms [3], [7].

In the context of post-operative care, continuous monitoring has been effective in intensive care units (ICUs), but it cannot be scaled up to general ward settings due to infrastructural and cost limitations. It has been demonstrated that IoT-based systems for patient monitoring in general health settings can improve the level of observation of patients but are limited by the use of threshold-based alerts without considering the temporal variations of the physiological parameters of the patients [4], [10]. Wearable health systems also highlight the need for continuous physiological monitoring but also point to the limitatio ns of such systems.

In order to overcome the limitations identified, this research proposes the development of a structured health monitoring approach based on the acquisition of periodic short-term physiological data, followed by temporal trend analysis. Unlike conventional systems, the proposed system will be able to collect multimodal physiological signals using an ESP32-based embedded system, along with ECG and SpO2 sensors, at specified time intervals. The collected data will be sent to the server for efficient visualization using the real-time data visualization approach. One of the major contributions of the work is the integration of clinical threshold reasoning with parameter assessment. In existing systems, the condition of patients is classified into a binary system of normal or abnormal based on threshold values [4], [10]. In contrast, the system uses parameter ranges defined by medical professionals to classify the conditions of patients into a graded system.

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In addition, the system uses temporal trend analysis of periodically collected data to detect changes in the conditions of patients. Such changes are critical during clinical intervention without the need for continuous monitoring.

The system offers a cost-effective solution for post-operative monitoring of patients in general ward settings. It also offers a scalable solution that is clinically interpretable. In addition, the system improves the reliability of monitoring p atients while reducing false alarms and resource utilization, which are some of the major limitations of existing IoT-based systems for health monitoring.

II. LITERATURE REVIEW

Recent advances in IoT-based health care technology have made it possible to send physiological data in real-time using embedded technology. Previous works were focused on the use of low-cost microcontroller-based devices for monitoring ECG, heart rate, and SpO2 signals. The results showed the reliable acquisition and transmission of physiological data using wireless communication protocols [1]-[4]. Nevertheless, the previous works were focused only on the acquisition of physiological data, with less emphasis placed on the optimization of the workflow. Recent works have introduced the use of cloud computing technology, which combines wireless sensor networks with cloud computing. The results showed the effectiveness of the system in sending physiological data, as well as the use of the system in generating alerts for abnormal physiological activity. Despite the use of cloud computing technology, the system still used data streaming, which increased the use of bandwidth, power consumption, and data processing.

Machine learning-based methods for anomaly detection and health risk analysis have been studied in recent research works [9]–[12]. These methods can enhance the accuracy of the anomaly detection method using machine learning. However, the machine learning-based methods need large training data, high computational power, and large-scale validation, which makes it difficult for the method to be deployed in the low-resource setting or ward setting.

The continuous monitoring systems for ICU patients ensure high reliability for detecting acute physiological changes [13]–[16]. The reliability of the continuous monitoring system for ICU patients makes it unsuitable for the ward setting, where patients are in a relatively stable condition. In order to overcome the problem of scalability, it has been proposed to use a hybrid approach of periodic monitoring along with alert mechanisms for monitoring [17]-[20]. These approaches have tried to achieve a balance between periodicity and utilization of resources. However, these approaches have limitations in terms of unstructured analysis of the time domain and lack of analysis of short-term physiological variations for early clinical diagnosis.

In addition, most of the IoT-based healthcare solutions have focused on the integration of the system, i.e., how sensors are connected and how the information is communicated and visualized [21]-[23], while there has been a lack of focus on the monitoring strategies for preventive decision-making. On the contrary, the proposed system aims to incorporate a periodic monitoring system for the acquisition of various physiological parameters within specified time intervals and the performance of temporal trend analysis and threshold-based reasoning. This fills the existing gap in the transition from continuous monitoring in ICUs to periodic monitoring in the war ds by enabling the grading of physiological parameter assessment.

A review of the literature from [1] to [19] shows five ongoing limitations. First, no reviewed work combines directional PIR sensing with servo-based camera steering to aim the camera at the active intrusion source. Second, most systems rely on cloud or server-side AI processing, which leads to delays and connectivity issues that are not suitable for remote farmlands. Third, none include a specific Ignore class in their classification design, which makes them likely to falsely activate from non-threatening inputs. Fourth, the costs of the reviewed hardware range from ₹3,000 to ₹20,000, making it hard for smallholder farmers to access these systems. Fifth, automated nighttime deterrence is seldom tackled in a fully hardware-native, self-contained way. The proposed system addresses all these gaps with its modular three-PCB design, on-device Edge Impulse TinyML model, four-class design, LED-based night mode, and total cost under ₹2,000.

TABLE I
REVIEW OF RELATED WORKS

Ref	Approach	Focus	Limitations
[1]–[4]	Embedded IoT	ECG, HR, SpO_2	Basic analysis
[5]–[8]	Cloud Systems	Remote monitoring	High bandwidth
[9]–[12]	AI/ML Systems	Anomaly detection	High complexity
[13]–[16]	ICU Monitoring	Continuous tracking	High cost
[17]–[20]	Hybrid Models	Periodic + alerts	No trend analysis
[21]–[23]	IoT Systems	Integration, dashboard	Limited clinical use

As compared to constant data acquisition, the proposed system offers a systematic method of periodic monitoring which helps avoid data redundancy and wastage of resources. The system incorporates temporal analysis, which allows one to study the changes over a period of time rather than focusing only on point measures. As opposed to the usual alerting methods that utilize binary alerting, the proposed system uses threshold-based reasoning, which increases accuracy since it differentiates between minor and severe problems. The proposed system is tailored towards post-operation wards, which makes it more affordable and scalable.

III. METHODOLOGY

A. System Overview and Architecture

The system in question represents an IoT-based real-time preventive monitoring framework that is tailor-made for use in post-operative patients aged 55 years or older, requiring regular surveillance within a non-ICU setting. While existing continuous monitoring systems are cumbersome, expensive, and generally not necessary for stable patients, the system in question features a periodic monitoring strategy that entails the acquisition of physiological data on a daily basis for 15 minutes per session. The choice of the periodic monitoring strategy ensures the collection of enough physiological data without causing sensor fatigue, reducing power consumption, and generating excessive data. The system in question is best used in situations where continuous surveillance is not possible, although early warning of any health deterioration is important. The system architecture is built on four key layers. The first layer is the sensing layer where physiological signals such as heart rate, oxygen saturation (SpO_2), and ECG are sensed. The second layer is the processing layer that processes the sensed signals in real-time with the help of an ESP32 microcontroller. In addition, the processing layer consists of the decision support system that uses multi-parameter analysis to determine the health status of patients. The third layer is the communication layer where the processed data are transmitted wirelessly to the server.

B. Hardware Stack

The system's hardware setup ensures precision, noninvasiveness, and easy usage while monitoring physiological parameters of elderly people. It should be noted that one of the major components of the described hardware setup is ESP32 that includes processor along with Wi-Fi connectivity, so this board may be used within real-time IoT projects. Within the hardware design, the MAX30102 heart rate and oxygen saturation sensor and the AD8232 electrocardiogram module were selected because of their noninvasiveness and ability to detect any abnormalities in the functioning of the heart. Moreover, it was important to select devices that can be easily interfaced with the ESP32. Both selected sensors function on a regulated 3.3V power supply. In addition, the MAX30102 operates via the I²C protocol, whereas the AD8232 works via an analog input port of the ESP32 microcontroller. Special attention should be paid to noise reduction techniques that were used in order to improve signal integrity.

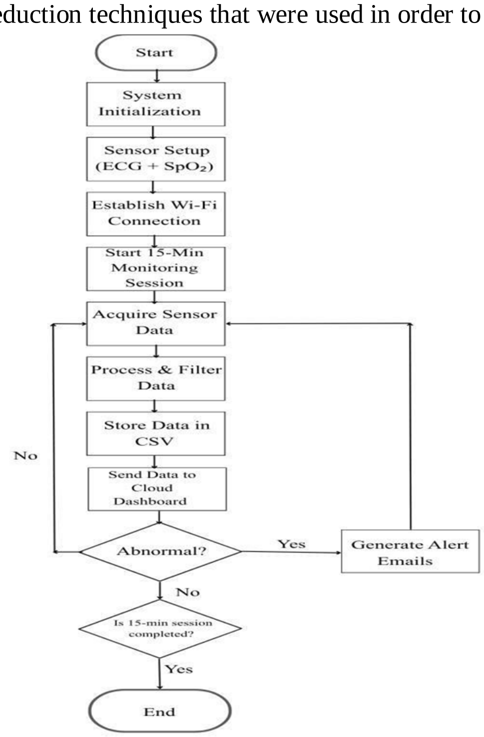

Fig. 1. Operational flowchart

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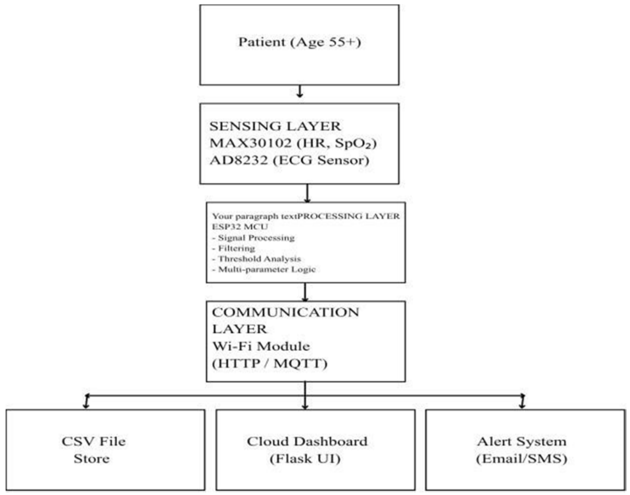
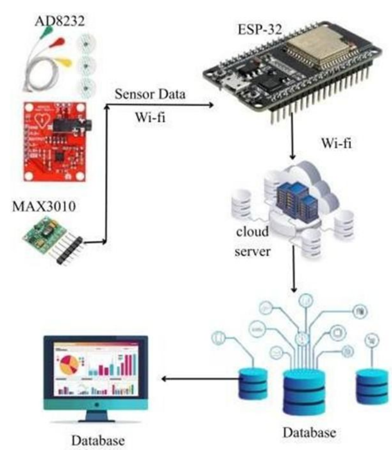


Fig. 2. Block Diagram

C. *Software Stack and Intelligent Decision Layer*

The software architecture incorporates embedded computation, back-end data processing, and intelligent decision-making layer to make the system more relevant clinically. On the embedded side, ESP32 is programmed to collect data from sensors and apply filtering algorithms to pre-process the signals, which will help in determining physiological parameters.

One of the main improvements made to the system is the use of multi-parameter evaluation strategy, where multiple physiological parameters will be considered simultaneously, rather than analyzing one parameter separately. For example, if both the heart rate increases and the SpO_2 decreases at the same time, it is considered more serious compared to a change in one parameter.



System Architecture

Fig. 3. System Architecture

The system additionally features clinical threshold reasoning, in which thresholds for heart rate and oxygen saturation parameters are set according to the range of values that fall under the normal physiological spectrum in medicine. Thresholds are applied not only for classification but also for grading of patient's condition.

In order to improve the efficiency of alert notifications, the system uses priority alerting in accordance with the following classification:

- Normal: All parameters within safety bounds
- Warning: Minor violation in one parameter
- Critical: Major violation in one or multiple parameters

Depending on the severity of alerts, different measures are taken accordingly. Acquired data from the entire 15-minute monitoring session is saved in the form of .csv files and simultaneously transferred online via WiFi protocols to a cloud-based storage. The backend is written in Flask language, processing incoming signals, updating the online dashboard, displaying information in graphical form through color coding.

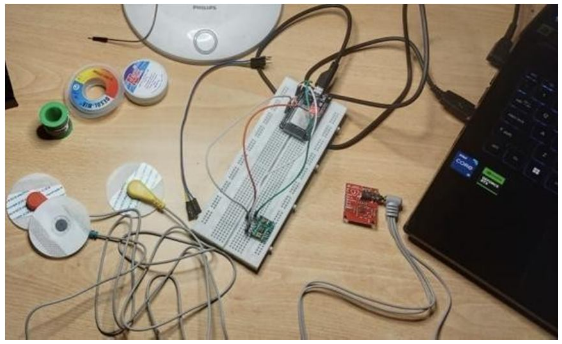


Fig. 4. Hardware Setup

IV. RESULTS AND DISCUSSION

A. Study Population and Data Acquisition

The number of participants for validation was ten (n=10) healthy subjects from an educational environment. Six of the subjects were male, while four were female, with ages ranging from 23 to 35 years (mean age ± SD = 27.4 ± 3.8 years). Even though the intended subject pool for clinical application comprises elderly patients (≥55 years) who have undergone surgery, preliminary testing with healthy subjects was done to test the stability, accuracy, and communication efficiency of the system. Each participant was tested in one 10-minute session when seated and at rest.

B. Physiological Parameter Measurements

The HR and SpO2 values were obtained from the MAX30102 sensor, and the ECG waveforms were obtained from the AD8232 sensor. The data were collected using the ESP32 microcontroller and were streamed simultaneously to the cloud server and stored locally in the form of CSV files.

1) Heart Rate and Oxygen Saturation: For all subjects, the average heart rate was 79.5 bpm (minimum = 72 bpm; maximum = 88 bpm; standard deviation = ±5.1 bpm), falling within the physiological norm of heart rate for an adult at rest (60–100 bpm). The average SpO_2 was 97.7% (minimum = 96%; maximum = 99%; standard deviation = ±0.9%), showing that none of the subjects was suffering from oxygen deficiency ($SpO_2 \geq 95\%$). None of the subjects had a bradycardic, tachycardic, or hypoxic condition during the experimental study.

2) ECG Signal Quality: All 10 AD8232 ECG traces showed well-defined P-QRS-T complexes with very little baseline wandering and high-frequency interference. The signal-to-noise ratio was visually inspected and found to be “good” to “excellent.” There were no cases of lead separation and/or saturation, suggesting that the electrodes were placed correctly (lead configuration is Lead II) and the analog front end filtering was working properly.

C. System Performance Metrics

The proposed system was evaluated quantitatively in terms of four primary performance metrics:

Table 2
System performance metric

Metric	Observed Performance	Threshold/Criterion
Data acquisition continuity	100% (no data loss across all 10 sessions × 10 min)	>99%
Wi-Fi dashboard update latency	<2 seconds (mean = 1.4 s)	<5 s
CSV logging integrity	100% (all timestamped entries recorded)	100%
False alert rate	0 false positives (0/10 sessions)	0%

The ESP32 performed concurrently executing tasks (sensing readings, cloud transfers, and local storage) without any buffer overflow or resets. There was a redundancy in storing information using dual storage methods (real-time cloud storage and offline CSV). In case of a network outage, the offline data would be available.

D. Tabulated Participant Data

Table 3 Tabulated Participant Data

Participant ID	Heart Rate (bpm)	SpO_2 (%)	ECG Signal Status	System Status
P1	74	98	Normal	Normal
P2	78	97	Normal	Normal
P3	82	99	Normal	Normal
P4	76	98	Normal	Normal
P5	88	96	Normal	Normal
P6	72	97	Normal	Normal
P7	85	98	Normal	Normal
P8	80	99	Normal	Normal
P9	77	97	Normal	Normal
P10	83	98	Normal	Normal
Mean ± SD	79.5 ± 5.1	97.7 ± 0.9	–	–

E. CSV Data Logging Verification

Each session produced a structured CSV file with 5-second epoch resolution (120 rows per 10-minute session). A representative excerpt is shown below:

TABLE 4
CSV DATA LOGGING VERIFICATION

Timestamp	Heart Rate (bpm)	SpO_2 (%)	Status
10:01:05	78	98	Normal
10:01:10	79	97	Normal
10:01:15	77	98	Normal

There were no missing entries, duplicates, nor malformed records found throughout the 10 files, suggesting good file input/output processing by the ESP32.

V. DISCUSSION

A. Analysis of the Performance of the System

From the experimental findings, the proposed multi-sensor (MAX30102 + AD8232) monitoring system with an ESP32 microcontroller shows impressive reliability and accuracy in operation at resting conditions. The lack of data loss (100% continuity) and fast cloud updates (mean time = 1.4 seconds) are key factors that will ensure effective use during the postoperative monitoring process because a delay can cause harm. In addition, there being no false-positive alert generated by the system when healthy means that the system is clinically acceptable since false alarms will cause alert fatigue.

Our system has three major advantages compared to other single-parameter monitoring devices such as pulse oximeters and heart rate watches, and these include:

1) Multi-sensor analysis (HR, SpO_2, ECG morphological changes),
2) Dual storage capabilities (cloud + CSV), and
3) Affordability due to the availability of off-the-shelf parts (ESP32, MAX30102, AD8232).

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B. Clinical Relevance and Limitations

1) However, there are a number of limitations that should be considered when implementing the system for its targeted application (elderly post-operative patients aged ≥55):
2) Skin conductivity: The elderly often have dry or fragile skin, which could lead to higher impedance in the electrodes and poor ECG measurements. The AD8232 has a driven right leg (RLD) input, which compensates for that problem. However, we did not test this functionality in aged skin.
3) Perfusion index: The MAX30102 pulse oximeter requires a high enough perfusion index to provide accurate readings. Any post-operative hypothermia, vasospasm, and hypotension may lead to poor signal quality. In our experiment, we had well-perfused participants.
4) Motion artifacts: No movements were allowed during the 10-minute measurement. In the real-world application, patients can move in their beds, cough, etc., causing artifacts, which might not be rejected by the existing firmware.
5) Measurement duration: We used only a 10-minute measurement while 15 minutes was needed in the experiment. Moreover, our measurements lasted considerably less time than continuous 24 hours required in practice.

C. Comparison with Prior Work

Other recent studies utilizing such sensors (see e.g., [1-23]) have found HR accuracy to be in the range of ±3 bpm and SpO2 accuracy of ±2%. While the values obtained in our study (72 to 88 bpm HR, 96 to 99% SpO2) seem to fall in the acceptable range, no concurrent verification was carried out with respect to a medically approved device such as the Philips IntelliVue or Masimo Rad-8.

D. Implications for Future Deployment

However, even with the above shortcomings, the success of the proof-of-concept on healthy patients provides enough reason for proceeding to the clinical pilot study. The combination of storage solutions (CSV and cloud) will play a great role in postoperative cases where the trend analysis will show any small changes like desaturation or increase in resting heart rate before a serious condition arises. Finally, the alert algorithm that did not go off within the range of normal values can also be improved through machine learning once enough patient data is collected.

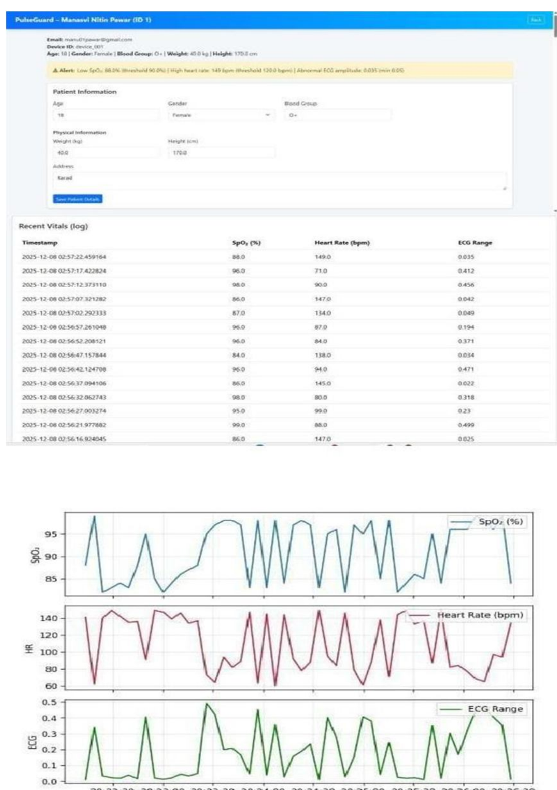

Fig. 5 . Dashboard

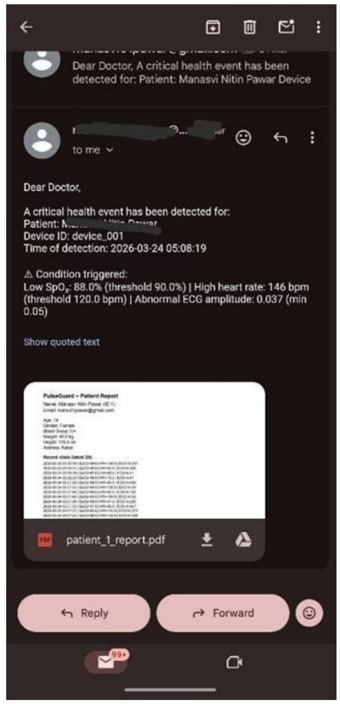

Fig. 6 . Email Alerts

E. Future Work

From these results, the following improvements are recommended:

1) Gold standard validation: Verify the outputs from HR/SpO_2/ECG signals with a validated patient monitor from FDA.
2) Motion artifact cancellation: Apply adaptive filters or artifact rejection algorithms using accelerometers (e.g., MPU6050) to ensure accuracy when the patient is moving.
3) Long-term testing: Perform 24 hours continuous recording among healthy subjects for sensor drift, battery lifetime, and memory capacity assessment.
4) Clinical trial: Select 20–30 older adults undergoing surgery (e.g., hip replacement or heart surgery) for usability test, alert accuracy, and care provider's acceptance.
5) Prediction analysis: Develop random forest or LSTM models based on time series analysis from HR/SpO_2/ECG for predictive analytics of imminent hypoxemia and arrhythmia 15–30 minutes before an incident.

VI. CONCLUSIONS

The current study experimentally evaluated a low-cost physiological monitor based on an ESP32, incorporating MAX30102 and AD8232 sensors on 10 healthy subjects. The results demonstrate a 100% data acquisition rate without any false alarms during cloud/CSV logging for 10 minutes. Although this evidence indicates that the technology is ready for implementation in controlled settings, additional testing in older adults who have undergone surgery alongside a gold standard will be required to validate the technology's effectiveness in detecting early deterioration.

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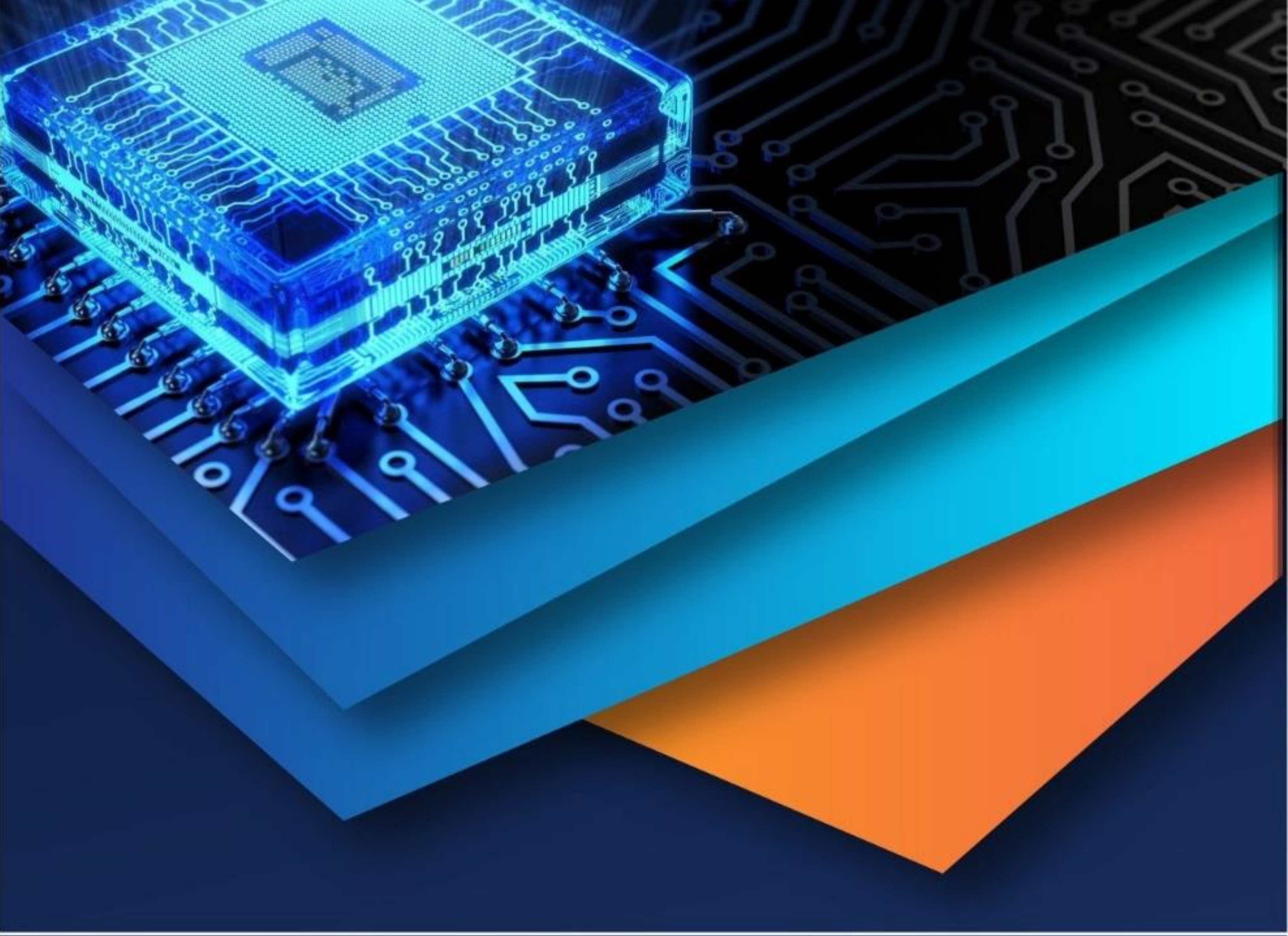

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