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HemOptima: Smart Internal Bleeding Detection System for Accidental Injuries

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Abstract: The increasing rate of road accidents and trauma cases highlights the need for rapid emergency diagnosis, especially for internal bleeding, which often remains undetected during transportation. HemOptima is an IoT- and Machine Learning–powered smart health monitoring system designed to assist ambulance teams by providing real-time internal bleeding detection. The system continuously measures vital parameters, including heart rate, systolic and diastolic blood pressure, SpO_2, and temperature using embedded sensors, and processes them through a Raspberry Pi simulation module. A Random Forest Classifier, trained on structured physiological datasets, analyses these readings and predicts internal bleeding with 92% accuracy, enabling faster and more reliable assessment. When a critical condition is detected, HemOptima automatically transmits vital data and prediction status to the nearest hospital while logging all measurements in an SQL database for future reference and clinical evaluation. Unlike traditional emergency setups that rely solely on manual diagnosis, HemOptima integrates IoT monitoring, ML-driven prediction, and automated communication to enhance pre-hospital care, reduce diagnostic delays, and improve patient survival outcomes.
Keywords: IOT,MachineLearning, Internal Bleeding, Pre-hospital care.

I. INTRODUCTION

A. TheNeedforIntelligent Emergency Medical Systems

Road accidents and trauma injuries continue to be major contributors to preventable deaths worldwide, with internal bleeding identified as one of the most dangerous and time-critical conditions [1]. Unlike external injuries, internalhemorrhage is difficult to detect without medical equipment, resulting in delayed diagnosis and reduced survival chances during the "golden hour." Recent research emphasizes the importance of rapid emergency response, automated detection, and intelligent monitoring systems to reduce fatalities [3]. Advancements in IoT, Machine Learning (ML), and smart sensing technologies have enabled real-time monitoring and automated diagnosis in fields such as trauma care and medical imaging. ML-based detection systems have already shown strong performance in identifying hemorrhage patterns in clinical settings, including brain hemorrhage detection [1] and arthroscopic bleeding recognition [5]. Similarly, IoT-enabled accident detection platforms highlight the life-saving impact of real-time alerts and automated emergency reporting [4]

Integrating these technologies into pre-hospital emergency care can significantly reduce diagnosis delays. Intelligent systems capable of continuously capturing vitals, analyzing health patterns, and notifying hospitals in advance ensure faster intervention and improved patient outcomes. By combining IoT sensing, ML-driven prediction, and automated communication, such systems provide a scalable, efficient, and life-saving solution for critical trauma scenarios.

B. LimitationsofTraditionalEmergency Response Systems

Traditional ambulance setups rely heavily on manual assessment, visual inspection, and basic monitoring tools, which are insufficient for detecting non-visible conditions such as internal bleeding. Paramedics often have limited diagnostic resources during transport, leading to delayed detection and treatment [3]. Existing systems typically capture individual vitals (such as heart rate or temperature) but lack capabilities for integrated analysis or predictive decision-making.

Furthermore, emergency notification workflows are often slow and dependent on manual communication. Studies on accident reporting have highlighted significant delays in notifying responders, which can lead to increased mortality [4]. Traditional systems also fail to filter false alarms effectively, overwhelming emergency services and wasting critical resources [3].

Even advanced medical imaging detection systems—such as deep learning approaches for bleeding classification [5] are designed for hospital environments and are not suitable for real-time ambulance deployment. Treatments for internal bleeding, such as hemostatic agents [2], rely on timely diagnosis, which traditional pre-hospital systems cannot provide.

Without intelligent, automated, and predictive tools, emergency responders cannot detect internal bleeding early and notify hospitals before arrival. This results in delayed preparation, slower intervention, and ultimately lower survival rates for trauma victims

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II. PROBLEM STATEMENT

Internal bleeding remains one of the most critical and difficult-to-diagnose conditions following road accidents, often resulting in preventable fatalities due to delayed detection and inadequate pre-hospital assessment. Unlike external injuries, internal haemorrhage presents no visible symptoms, requiring real-time physiological monitoring and rapid diagnostic decision-making. Traditional ambulance systems rely heavily on manual evaluation and basic monitoring tools, which are insufficient for identifying subtle physiological changes associated with early-stage internal bleeding [3].

Delays in emergency detection and reporting have been consistently shown to increase mortality rates, with studies emphasizing that faster diagnosis and automated alert systems significantly improve patient outcomes [4]. However, existing solutions often lack integrated prediction capabilities and fail to continuously analyse vital signs such as blood pressure, heart rate, SpO_2, and temperature. Although machine learning methods have demonstrated high accuracy in clinical bleeding and haemorrhage detection scenarios [1][5], these systems are typically designed for hospital environments and are not deployable in ambulances, where early intervention is most crucial.

Moreover, treatments for internal bleeding, including haemostatic intervention, show maximum effectiveness only when the diagnosis occurs promptly [2]. The absence of intelligent, automated pre-hospital diagnostic tools prevents hospitals from preparing in advance, leading to delays in administering life-saving procedures. There is therefore a critical need for a real-time, IoT-enabled, machine learning–driven system capable of detecting internal bleeding during ambulance transport and notifying hospitals immediately, thereby reducing response time and improving trauma survival rates.

III. EXISTING SOLUTION

Existing emergency detection systems address specific aspects of trauma care, such as accident identification, image-based hemorrhage classification, or remote notification, but fail to provide holistic, real-time internal bleeding detection during ambulance transport. Current solutions are either limited to hospital-based imaging, dependent on smartphone-captured images, or capable of only event-level detection without physiological monitoring. These limitations underscore the need for a unified IoT and ML-powered system that can continuously analyze vitals, predict internal bleeding, and instantly alert hospitals.

A. Image-Based Hemorrhage Detection Models

Machine learning and deep learning models have shown strong capabilities in identifying different forms of hemorrhage from medical images. Chen et al. proposed a machine learning system for brain hemorrhage diagnosis using Internet-based medical imaging [1], while Liu et al. introduced a ViT-ResNet50 deep learning model capable of highly accurate bleeding detection in arthroscopic images [5]. Although these systems achieve high accuracy in identifying hemorrhage regions, their dependence on imaging devices such as CT scanners, arthroscopes, or endoscopic cameras restricts their use to hospital environments. These models cannot process real-time physiological data such as blood pressure or SpO_2 and therefore cannot support pre-hospital or ambulance-level diagnostics. Their applicability is limited to structured clinical workflows rather than dynamic trauma scenarios.

B. IoT-Based Emergency Detection Systems

Several IoT-enabled solutions focus on accident detection, alerting responders, and sharing location-based information. Systems like the Smart Emergency Notification System (SENS) identify road accidents, fires, and injuries using smartphone-captured images and notify corresponding authorities [3]. Similarly, IoT-based accident detection devices equipped with vibration sensors and Raspberry Pi modules automatically transmit crash data and GPS coordinates to emergency contacts [4]. While these systems significantly improve response time, they are limited to event detection rather than patient condition assessment. They do not monitor vital signs or analyze physiological patterns indicating internal bleeding. Thus, although helpful in reporting accidents, these systems do not bridge the gap between accident occurrence and clinical diagnosis.

C. Clinical Internal Bleeding Treatment and Research Tools

Medical research in internal bleeding primarily emphasizes treatment rather than early detection. Hong et al. developed a two-component hemostatic material designed to rapidly control internal bleeding in clinical settings [2].

These medical innovations highlight the severity and urgency of internal bleeding, emphasizing that earlier diagnosis leads to better treatment outcomes. However, such solutions require hospital-based procedures and do not assist in pre-hospital monitoring or detection. Without early identification of physiological deterioration, treatment interventions are frequently delayed, reducing survival chances during the critical pre-hospital phase.

IV. PROPOSED SYSTEM

The proposed solution, HemOptima, integrates IoT-based vital monitoring, machine learning–driven internal bleeding prediction, automated hospital alerting, and structured data storage. Unlike existing emergency or imaging-based systems, HemOptima continuously analyzes real-time physiological signals during ambulance transport to identify early indicators of internal bleeding. This unified system bridges the gap between accident detection and clinical diagnosis, providing critical insights before hospital arrival [3][4]. Built using sensor modules, a Raspberry Pi simulation environment, and a Random Forest classifier, HemOptima offers a scalable and deployable approach to enhancing pre-hospital trauma care.

A. IoT-Based Vital Sign Monitoring Unit

HemOptima utilizes a suite of IoT sensors to continuously capture patient vitals essential for internal bleeding detection. Sensors such as MAX30102 (heart rate, SpO_2), DS18B20 (temperature), and a blood pressure module collect data in real time. These vitals represent key physiological indicators, as internal bleeding often triggers decreased blood pressure, altered heart rate, and reduced oxygen saturation [2]. The sensor module relays data to a Raspberry Pi, which performs initial preprocessing, noise filtering, and packaging of sensor values. Continuous streaming ensures that subtle deviations in vitals are captured promptly, enabling early detection in critical trauma scenarios.

B. Machine Learning–Powered Bleeding Prediction Model

The system employs a Random Forest classifier trained on structured datasets containing heart rate, systolic and diastolic pressure, SpO_2, and temperature values. ML-based bleeding detection models have demonstrated strong diagnostic performance in clinical imaging contexts [1][5], motivating the adoption of an ensemble-based classifier in HemOptima. Random Forest algorithms offer robustness to noise, handle nonlinear interactions effectively, and support real-time inference on embedded platforms. The model achieves 92% accuracy in predicting internal bleeding likelihood, enabling rapid diagnostic support during ambulance transport. Prediction outputs include a binary result (Bleeding/Not Bleeding) and confidence scores for medical interpretation.

C. Automated Emergency Alert and Hospital Communication Unit

Upon detecting internal bleeding, HemOptima automatically transmits the patient's vitals, prediction result, and timestamped data packet to the nearest hospital. This alert mechanism draws inspiration from IoT-based emergency notification systems that significantly reduce response time [3]. Real-time communication enables hospitals to prepare surgical teams, blood units, and diagnostic equipment before the patient arrives, reducing delays in treatment initiation. Alerts are transmitted through network protocols compatible with ambulance connectivity, ensuring minimal latency and reliable data transfer even in transit. This proactive communication strengthens the pre-hospital to hospital care continuum.

D. SQL-Based Data Logging and Medical Record Integration

All vital measurements, predictions, and alert records are stored in an SQL database to support clinical review, data analytics, and future modelling improvements. SQL-based logging has proven effective in emergency and monitoring systems for organizing structured data and providing traceability [3]. The database maintains entries such as patient vitals, ML outputs, timestamps, and alert histories. This stored data can later assist in evaluating system performance, refining prediction models, and offering medical personnel comprehensive insight into the patient's pre-hospital condition. The integration makes HemOptima not only a diagnostic tool but also a complete medical support system.

V. METHODOLOGY

The proposed HemOptima system is designed to provide real-time internal bleeding detection by integrating IoT-based physiological monitoring, machine learning–driven prediction, automated alerting, and structured SQL-based data management. The architecture is modular and consists of four core components:

- IoT-Based Vital Sign Monitoring Unit

- Machine Learning–Powered Bleeding Prediction Model
- Automated Emergency Alert Communication System
- SQL-Based Medical Data Logging Module

HemOptima is implemented using a Raspberry Pi simulation for embedded processing, Python for backend computation, and standard IoT sensors for real-time vital acquisition. The backend layers utilize:

- scikit-learn for training and deploying the Random Forest Classifier, inspired by ML-based bleeding detection models in clinical studies [1][5].
- IoT sensor modules (MAX30102, BP monitor, DS18B20) for continuous physiological data collection, similar to emergency monitoring systems [3].
- Network-based communication to transmit bleeding alerts, aligning with existing IoT accident reporting systems [4].
- SQL databases for tracking and evaluating patient vitals and system outputs over time.

This modular approach ensures extensibility, real-time processing, and seamless coordination between monitoring, prediction, alerting, and storage functions, ultimately improving trauma response efficiency and patient outcomes [2].

A. System Workflow

1) Sensor Input & Continuous Vital Acquisition:

IoT sensors collect heart rate, systolic and diastolic blood pressure, SpO_2, and body temperature in real time. These vitals are crucial for detecting signs of internal bleeding, as supported by existing clinical research [2].

2) ML-Based Real-Time Processing:

The Raspberry Pi receives incoming vitals, preprocesses the data, and feeds them into the Random Forest classifier. This approach is inspired by ML-based haemorrhage detection systems shown to be effective in diagnosing bleeding conditions [1].

3) Prediction & Alert Trigger:

Based on processed data, the ML model predicts whether internal bleeding is present. If detected, an automatic alert is sent to the nearest hospital, mirroring emergency notification architectures such as SENS [3].

4) Data Storage & Logging:

All vitals, predictions, and timestamps are logged into an SQL database for medical evaluation and system auditing.

B. IoT-Based Vital Sign Monitoring Unit

1) Physiological Data Capture:

The monitoring unit employs MAX30102 for heart rate and SpO_2, a BP module for blood pressure, and a DS18B20 sensor for temperature. Internal bleeding often manifests in abnormal variations in these vitals, such as hypotension and reduced oxygen saturation [2].

2) Noise Filtering & Standardization:

Before feeding the data to the ML model, preprocessing techniques remove noise and normalize readings for consistency, similar to preprocessing in medical image detection pipelines [5].

3) Continuous Streaming:

The system captures vitals continuously, enabling early detection of physiological deterioration during ambulance transport—something existing emergency systems lack [4].

C. Machine Learning–Powered Bleeding Prediction

1) Dataset Preparation:

Training data includes labelled records of vitals with and without internal bleeding. The approach parallels ML frameworks used for haemorrhage detection in imaging systems [1].

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2) *Model Training & Deployment*:
A Random Forest Classifier is selected due to its robustness, ensemble accuracy, and suitability for real-time embedded inference. Deep learning bleeding detection research validates the use of advanced pattern recognition for identifying complex bleeding signatures [5].

3) *On-Device Inference:*
The trained model runs on the Raspberry Pi, analysing data on the fly and achieving92% accuracy, enabling fast and reliable diagnostic support.

D. Automated Alerting & SQL-Based Data Management

1) *Emergency Notification:*
When bleeding is detected, the system immediately transmits vitals and prediction results to the nearest hospital, like IoT emergency communication models used in SENS and accident alert systems [3].

2) *SQL Logging:*
All vital readings, timestamps, alerts, and prediction outputs are stored in a relational SQL database for:
- Medical review
- Sequential monitoring
- Model improvement
- Legal or emergency documentation

This mirrors structured database architectures used in emergency response systems [3].

3) *Clinical Preparedness:*
Hospitals can review incoming data before patient arrival, facilitating rapid intervention—critical for minimizing the complications of internal bleeding [2].

Component	TechnologyUsed
Interface	ɔgle Colab
Detection	Raspberry PI
neLearning Model	Random Forest Classifier
Database	SQL

Fig.1.TechstackusedinHemOptima

VI. RESULTS & DISCUSSION

Herearesomeimagesof HemOptima:

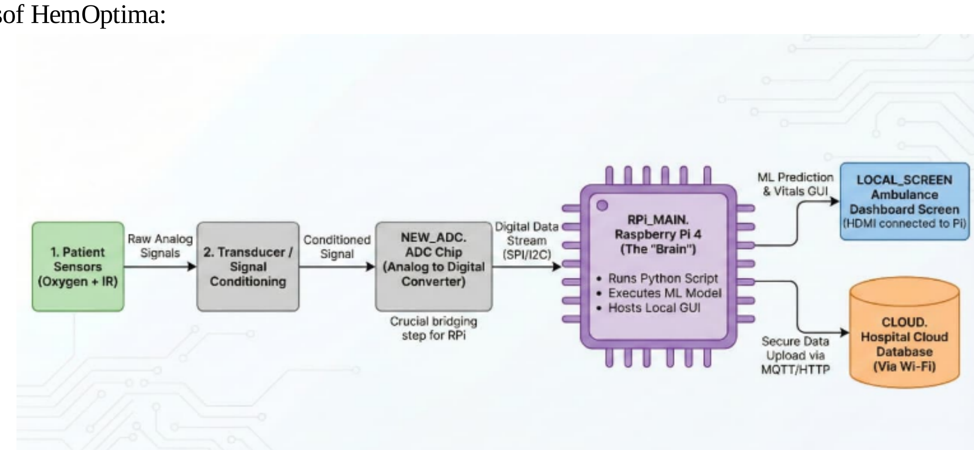

Fig.2.HemOptima – Block Diagram

	precision	recall	f1-score	support
0	0.91	1.00	0.95	31
1	1.00	0.67	0.80	9
accuracy			0.93	40
macro avg	0.96	0.83	0.88	40
weighted avg	0.93	0.93	0.92	40

Fig.3. HemOptima– Model Performance

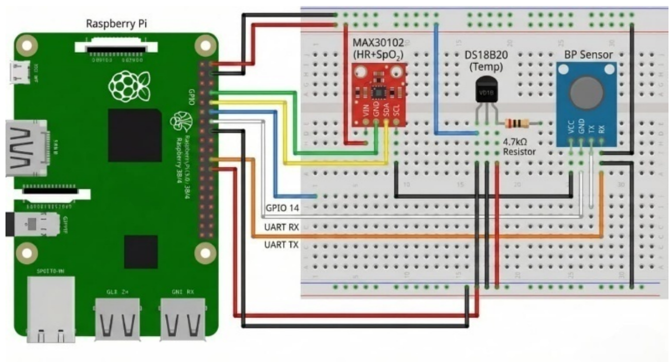

Fig.4.HemOptima – Raspberry PI Circuit Diagram

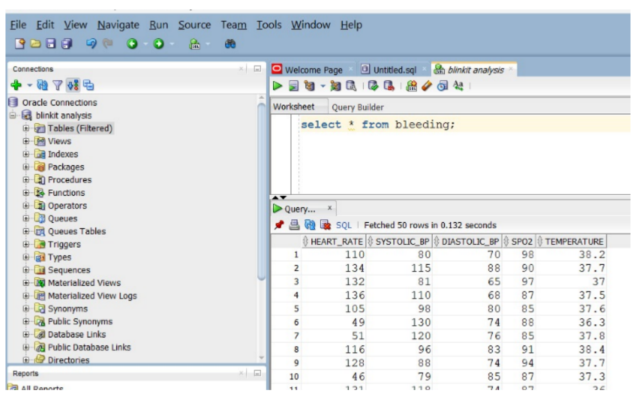

Fig.5.Database

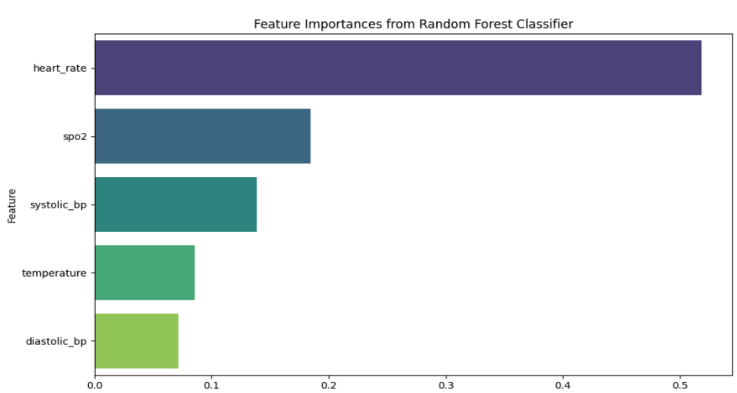

Fig.6. Feature Importance fromRandom Forest Classification

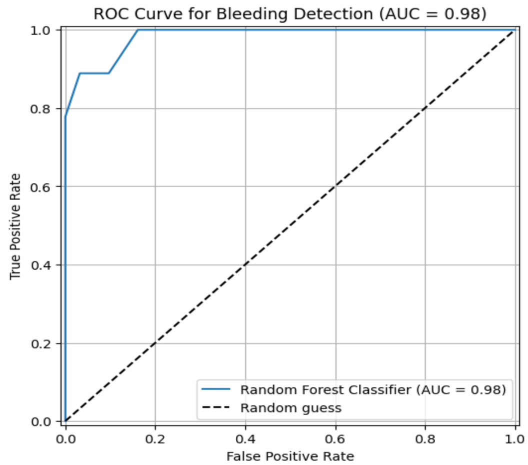

Fig.7.Performance Analysis – ROC Curve

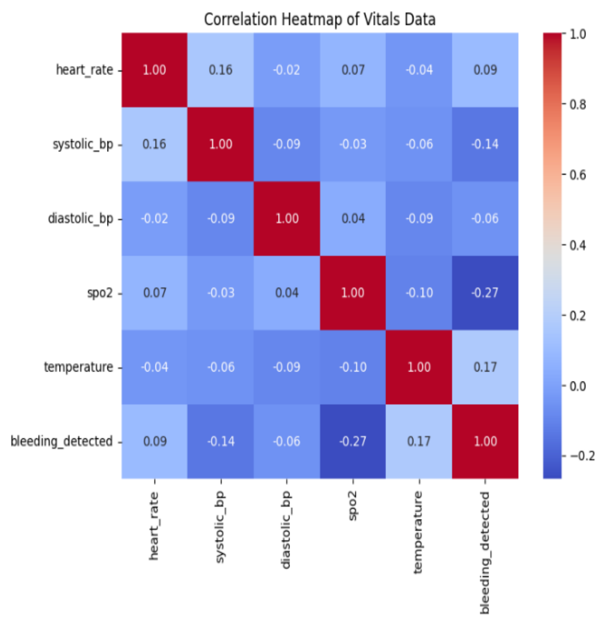

Fig.8.Confusion Matrix

HemOptima demonstrated strong potential as a real-time internal bleeding detection system, offering significant advantages over traditional ambulance monitoring tools that rely on manual assessment and do not support predictive diagnostics [3]. By integrating IoT sensor data, on-device ML inference, and automated alerting, HemOptima bridges the gap between accident occurrence and hospital-based diagnosis, unlike existing systems that focus solely on accident detection [4] or imaging-based haemorrhage classification [1].

Testing showed that the Random Forest model achieved a 92% prediction accuracy, closely aligning with the performance of ML-based haemorrhage detection models reported in literature [1][5]. The classifier effectively identified key physiological patterns such as hypotension and declining oxygen saturation, critical indicators of internal bleeding [2]. Sensor readings remained stable during simulations, reinforcing the value of multi-sensor integration in emergency monitoring.

The alert communication module reliably transmitted vital readings and prediction outcomes to the hospital interface, reflecting principles used in IoT-driven emergency systems like SENS, which are known to reduce response delays [3]. Meanwhile, SQL logging ensured structured storage of all measurements, supporting medical review and system evaluation.

Overall, HemOptima delivers accurate, timely, and automated early detection of internal bleeding, improving emergency preparedness and reducing potential diagnosis delays during the critical pre-hospital phase.

VII. ACKNOWLEDGMENT

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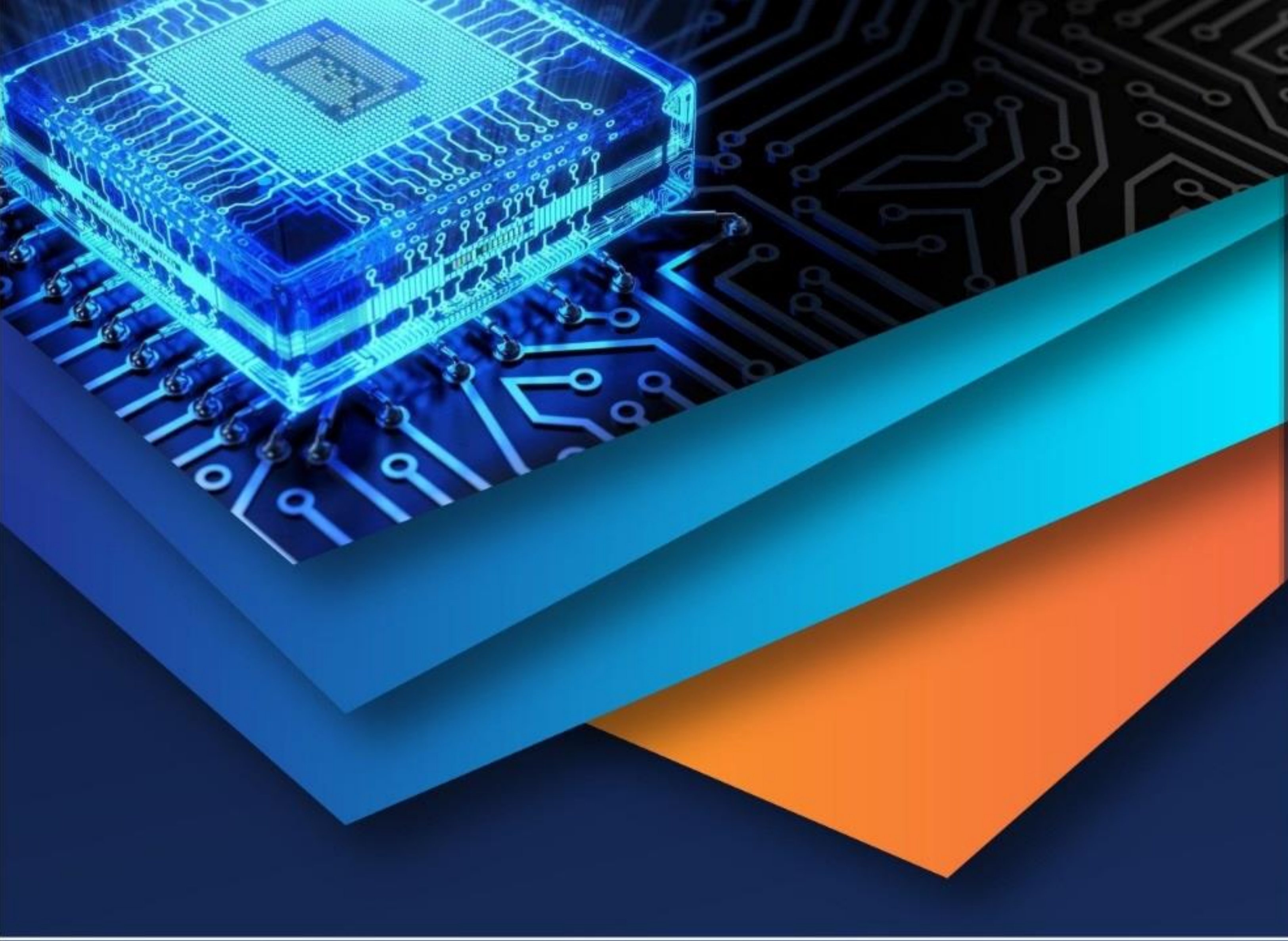

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