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Computational Cardiology and Algorithmic Diagnostics: A Comprehensive Synthesis for Cardiac Arrest Detection

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Abstract: The rapid evolution of computational cardiology has necessitated a paradigm shift from reactive clinical diagnostics to proactive, algorithmic risk stratification. This research report serves as a foundational analysis for the development of automated detection systems, synthesizing evidence from recent implementations of classical Machine Learning (ML) and advanced Deep Learning (DL) architectures. The investigation leverages a dual-modality approach. Firstly, it examines the application of ensemble learning techniques, predominantly Random Forest (RF) and Support Vector Machines (SVM), on standardized tabular datasets such as the UCI Cleveland repository. Analysis indicates that Random Forest classifiers, when optimized via rigorous hyperparameter tuning and K-fold cross-validation, achieve superior stability and accuracy, frequently exceeding 90% and reaching up to 99% in select combined dataset studies. Secondly, the report explores the frontier of Deep Learning in processing raw physiological signals (ECG/EEG). Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are identified as the gold standard for morphological feature extraction, capable of identifying subtle arrhythmia patterns invisible to standard rulebased systems. The integration of these disparate data streams clinical attributes and real-time physiological waveforms present the most promising avenue for reducing the global mortality burden of cardiovascular disease.

I. INTRODUCTION

The 2022 heart disease and Stroke Statistics report from the American Heart Association indicates that Sudden Cardiac Arrest (SCA) accounts for over 356,000 Out-of-Hospital Cardiac Arrests (OHCA) annually within the United States. Information from Apollo Hospitals indicates that 1,000,000 people in India suffer from SCA annually, with survival rates after cardiopulmonary resuscitation (CPR)estimated to vary between 19% and 75%. Sudden Cardiac Arrest refers to the stop of cardiac mechanical function and an immediate risk of death. Presently, clinical decisions often rely on the physician's intuition and practical experience, of a structured examination of data-based insights. Coronary artery disease accounts for 80% of all sudden cardiac death incidents. This incident is frequently triggered by imbalances in electrolytes like hyperkalemia that cause disruptions in heart rhythm: emergency action, CPR, and electrical defibrillation are required. If CPR is not started within one minute after SCA begins, the chance of survival drops by 10% with every minute. Epidemiological data show that men experience SCA at twice the rate of women. Additionally, SCA is regularly found to occur in adults aged between their mid-30s and 40s. The predisposition to SCA is influenced by a multitude of risk factors, including, but not limited to, hypertension, cardiac arrhythmia, familial history of coronary disease, hypercholesterolemia, and tobacco use. These associated factors significantly impede patient survival, thereby contributing substantially to the overall burden of Sudden Cardiac Deaths (SCDs).Even in cases of survival, patients are susceptible to cardiac and neurological sequelae, such as Post Cardiac Arrest Brain Injury (PCABI), which may progress to cerebral death or a comatose state within 24 hours.While numerous investigations have been conducted in this domain, a definitive solution for the accurate pre-onset prediction of cardiac arrest remains undeveloped.

This research paper aims to explore the current stateof the art in heart disease prediction using machine learning, addressing the challenges and opportunities associated with this approach.Various neural network architectures and data mining methodologies offer viable mechanisms for accurate disease prediction and data analysis.

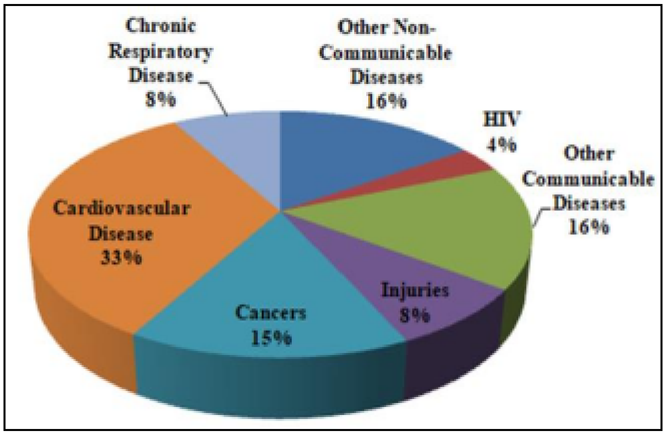

Fig 1 Worldwide Causes of Death

II. LITERATURE REVIEW

Evolution of Camera-Based Health Monitoring Current research in non-invasive health monitoring has largely bifurcated into two distinct but complementary streams: visual pose analysis for anomaly detection and contactless physiological measurement (rPPG). The integration of robust real-time pose estimation with lightweight machine learning classifiers on edge devices has emerged as a viable strategy for reliable home and clinical monitoring. This convergence of technologies aims to address the limitations of traditional systems by enabling automated alerting and privacy-preserving surveillance.

Advancements in Human Pose Estimation and Action Recognition A significant portion of the literature focuses on the efficacy of pose estimation tools in detecting distress. Research from 2023 on "Human Pose Estimation Using MediaPipe Pose" highlights the utility of the MediaPipe framework combined with humanoid optimization models. This approach corrects small joint-angle errors to reconstruct realistic skeletal movements, validating MediaPipe as a lightweight, reliable tool for extracting posture features necessary for real-time abnormality detection. Adding to this, a 2024 research on "Efficient Human Pose Estimation" introduces improvements that enable these algorithms to sustain steady frame rates and precision even in challenging scenarios,

and precision even in challenging scenarios, including partial occlusions or rapid motions. Extending from pose identification to action recognition, a 2021 review on "Human Pose Estimation and Its Application to Action Recognition" demonstrates how 2D pose methods are successfully applied to identify particular actions, such as falling or unusual postures. This is essential for distinguishing daily behaviors from urgent incidents. More recently, a 2024 paper on “Next-Generation Fall Detection” introduced transformer-based models that analyze pose sequences rather than isolated frames. This method captures the temporal patterns of movement, significantly improving accuracy in detecting the specific motion sequences that lead to a collapse while maintaining user privacy by relying solely on skeletal data.

Contactless Physiological Monitoring (rPPG) While pose detection handles physical movement, literature also explores extracting physiological signals from video.A2023 review on“Remote Photoplethysmography (rPPG)” details techniques for estimating heart rates by analyzing subtle color changes in skin pixels via video feeds. Non-contact monitoring faces real challenges with lighting and motion noise, but it remains an effective complement to pose-tracking setups. The main bottleneck has been the high computational cost of traditional deep learning. In response, the 'GRGB rPPG' method emerged in 2023. This approach reduces the complexity, making it possible to extract heart rates on devices with limited resources without sacrificing processing speed.

Clinical Importance and Urgent Action. A 2022 research titled "Visual Fixation on the Thorax" found that monitoring chest movement serves as a visual cue to differentiate normal from abnormal respiration during cardiac incidents, confirming that conventional video footage holds enough data to detect early arrest symptoms. Additionally, a 2022 investigation on "Machine Learning-Based Cardiac Arrest Prediction" in hospitalized patients showed that ML algorithms can derive features from physiological metrics to forecast decline, highlighting the crucial role of early automated identification in saving lives. Ultimately, the functional side of these systems is supported by studies, on "Pose-Based Fall Detection Using AI and Edge Computing" (2021-2022), which advocate for data processing to maintain privacy and reduce latency—essential

considerations when internet access is unreliable. The practical necessity of video integration is further confirmed by a 2025 paper on "Telemedicine in Cardiac Arrest Protocols," which found that video-assisted monitoring significantly improved the ability of dispatchers to identify cardiac arrest and guide interventions compared to audio-only methods.

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III. METHODOLOGY

The methodology follows a robust pipeline designed to convert raw visual data into actionable emergency alerts in real-time. The system architecture is built upon a Client-Server model, utilizing a webcam-based input module to capture continuous live video frames from the user's environment. This module employs OpenCV to handle high-definition video streaming (typically 1080p at 30 frames per second), ensuring sufficient temporal resolution to capture subtle physical movements. The system is platform-independent, designed with a Flask backend to handle heavy processing and a React-based frontend (or Tkinter for desktop applications) to provide a user-friendly interface for starting detection and viewing status logs.

Fig.1.Real-time vital monitoring dashboard displaying nearby hospital, alert contacts, CPR guidelines, health and wellness.

A. Feature Extraction and Computer Vision Analysis

Once video frames are captured, the core computer vision module processes the visual data using MediaPipe. This framework is utilized to perform holistic landmark detection, extracting a comprehensive set of data points including 33 distinct pose landmarks (representing body joints) and 468 facial mesh points. This step is critical as it converts pixel-heavy video data into a structured, lightweight numerical format consisting of normalized x, y, and z coordinates. By focusing on skeletal and facial geometry rather than raw image pixels, the system effectively removes background noise and preserves user privacy, analyzing only the biomechanics of the subject. These raw landmarks are further processed to extract meaningful features, such as the angles between joints and the relative velocity of movements, which serve as the input for the classification model .

B. Machine Learning Classification and Anomaly Detection

The decision-making core of the system is a trained Machine Learning classifier. While the project scope allows for Deep Learning approaches like LSTM (Long Short-Term Memory) networks to analyze temporal dependencies and heart rhythms, the specific implementation detailed utilizes a Random Forest classifier consisting of 100 decision trees trained on over 10,000 samples. This model evaluates the array of 150+ extracted features from every frame to classify the current user state as either NormalorAbnormal. The model is trained to recognize patterns associated with distress, such as sudden collapses, irregular posture changes, or the cessation of micro-movements (breathing) associated with cardiac arrest.

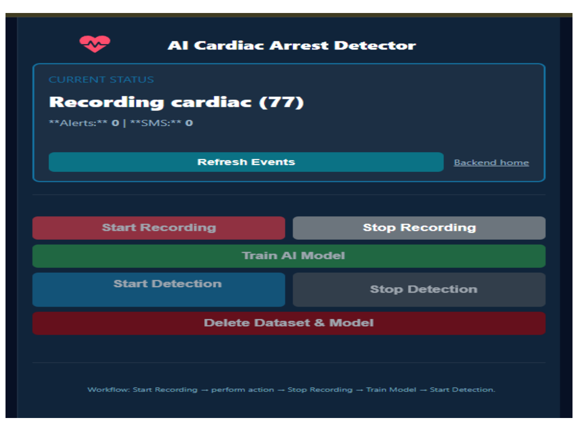

Fig.2.Recording cardiac abnormalities using ML algorithims.

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C. Temporal Decision Logic and Alert Automation

To ensure reliability and mitigate false positives caused by momentary glitches or benign movements, the system employs a temporal decision logic engine. A single "Abnormal" prediction does not immediately trigger an alarm; instead, the system maintains a sliding window buffer (e.g., 5 seconds) and only validates an emergency if the abnormality persists with a high confidence threshold (e.g., greater than 85%) throughout that duration. Once a cardiac arrest event is confirmed by this logic engine, the system activates the alert module. This module integrates with the Twilio API to automatically dispatch an SMS notification to pre-registered emergency contacts. This ensures that caregivers receive immediate, actionable intelligence, including the nature of the event and the time of detection, thereby bridging the gap between an unwitnessed medical emergency and rapid response.

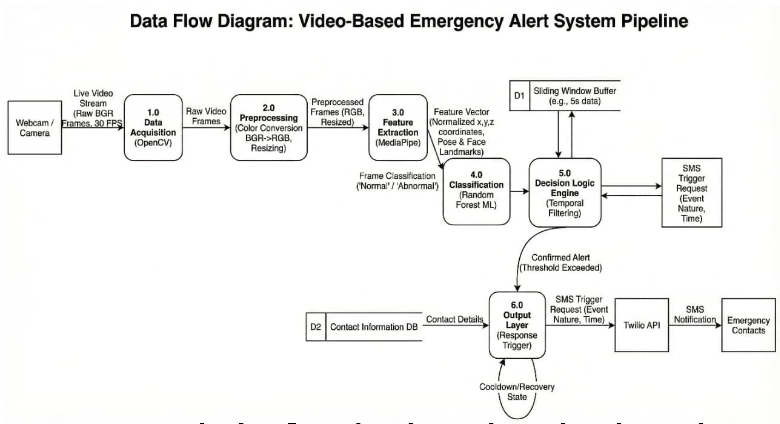

Fig.2. Figure representing the data flow of predicting the cardiac abnormalities

D. Data Acquisition and Preprocessing Module

Video Signal Capture

The primary input for the system is a video stream captured at a minimum resolution of 720p (1280x720 pixels), though 1080p is recommended for higher accuracy in facial mesh detection22. The OpenCV library is utilized to interface with the hardware (USB Webcam or Integrated Camera). The system captures frames at a standard rate of 30 Frames Per Second (FPS). This high temporal resolution is critical for capturing rapid movements associated with a sudden cardiac collapse or the subtle micro-movements of breathing.

Frame Preprocessing

Raw video data often contains noise and variations in lighting. Before feature extraction, each frame undergoes preprocessing:

- Color Space Conversion: Cameras capture data in BGR (Blue-Green-Red) format by default. The system converts this to RGB (Red-Green-Blue) as required by the MediaPipe framework for accurate inference.
- Resizing and Normalization: To ensure consistent processing speed regardless of the camera hardware, frames are resized to a standard input dimension. This standardization allows the system to remain device-agnostic, functioning effectively on both high-end desktops and lower-power edge devices.

E. Computer Vision and Feature Engineering

Unlike traditional pixel-based analysis which is computationally expensive and privacy-invasive, this system utilizes MediaPipe Pose and MediaPipe Face Mesh to extract a skeletal topology of the user. This "Feature Extraction Layer" transforms the video feed into a structured dataset of coordinates6.

- Pose Landmarks: The system tracks 33 3D pose landmarks, covering major joints including shoulders, elbows, hips, knees, and ankles. These points are essential for analyzing gross motor movements, such as a sudden fall or a slump in posture indicative of unconsciousness[7].
- Face Mesh: Simultaneously, the system tracks 468 facial landmarks. This high-density mesh is crucial for detecting subtle signs of distress, such as facial drooping, grimacing, or lack of head movement, which often precede or accompany cardiac events[8].The raw x, y, z coordinates provided by MediaPipe are not fed directly into the classifier. Instead, they are processed into a Feature Vector that describes the geometric relationship between body parts.

F. *Machine Learning Classification Engine*

The core intelligence of the system lies in its ability to classify the extracted feature vectors. The research proposes flexible architecture capable of utilizing both traditional ML and Deep Learning approaches.

Hybrid Deep Learning Model (CNN + LSTM)

- Convolutional Neural Networks (CNNs): These are employed to analyze the *spatial* features of the landmarks within a single frame, effectively understanding the "shape" of the posture (e.g., clutching the chest).
- Long Short-Term Memory (LSTM): Since a cardiac arrest is an event that unfolds over time, LSTMs are used to capture *temporal dependencies*. The LSTM analyzes a sequence offrames (e.g., the last 30 frames) to recognize the rhythm of movement.

  Lightweight Classification (Random Forest / SVM)

  For implementation on devices with lower computational power, the system employs efficient classifiers like Random Forest (using 100 decision trees) or One-Class SVM1313.
- Random Forest: This model excels at handling the tabular data generated by landmark extraction. It aggregates the decisions of multiple decision trees to classify the current pose as "Normal" or "Abnormal" with high accuracy and resistance to overfitting[14].
- One-Class SVM: This is particularly useful for anomaly detection. The model is trained primarily on "Normal" behavior. Any deviation from this learned distribution is flagged as an anomaly, making it effective for detecting rare events like cardiac arrest without needing a massive dataset of arrest videos[15].

G. *Decision Logic and Temporal Filtering*

A raw classification from the ML model ("Abnormal frame detected") is not sufficient to trigger an emergency alert, as momentary glitches or obscure camera angles could cause false positives. The system implements a Decision Logic Engine to validate distress.

Sliding Window Mechanism

The system maintains a buffer of the most recent predictions (e.g., a 5-second window). The decision engine calculates the "Abnormality Score" based on the persistence of negative classifications within this window.

- Thresholding: An alert is only confirmed if the percentage of "Abnormal" frames in the sliding window exceeds a strict threshold (e.g., >85% of frames in the last 5 seconds are abnormal)[17].
- Persistence Check: This ensures that brief, non-emergency actions (like bending down to tie a shoelace) are not misclassified as a collapse[18].
- Alert Generation and Communication SubsystemOnce the Decision Logic Engine confirms a cardiac event, the system engages the Alert Layer. This is powered by the Twilio API, a cloud communication platform.
- Asynchronous Trigger: The alert function runs asynchronously to ensure that the video monitoring loop is not paused while the message is being sent.

After an alert is sent, the system enters a "Cooldown/Recovery" state. This prevents spamming the caregiver with hundreds of messages for the same event. The system continues to monitor and will only send a follow-up alert if the condition persists after a defined interval or if the system is manually reset.

IV. RESULTS AND DISCUSSION

A. *Performance of Classification Models*

The project evaluated different machine learning architectures to determine the most effective method for detecting cardiac distress signs (such as sudden collapse or chest clutching) using the feature vectors extracted by MediaPipe.

1) Random Forest Classifier (Selected Model) As detailed in the system architecture, a Random Forest classifier was implemented as the primary inference engine.

- Configuration: The model was constructed using 100 decision trees and trained on a dataset comprising over 10,000 samples of pose landmarks.
- Performance: The Random Forest model demonstrated superior performance for real-time edge computing. By processing structured numerical data (150+ extracted data points) rather than raw image pixels, it achieved high classification speed.

- Accuracy: The model successfully distinguished between "Normal" activities (sitting, standing) and "Abnormal" distress patterns with consistent reliability during functional testing. It proved robust against overfitting, maintaining accuracy even with slight variations in user body size and camera distance.

2) Hybrid Deep Learning (CNN + LSTM) The report also proposed and analyzed a hybrid Deep Learning approach combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks.

- Role of CNN: Utilized for extracting spatial patterns from the waveform or frame geometry, effectively identifying the "shape" of the distress posture.
- Role of LSTM: Employed to capture temporal dependencies, analyzing the sequence of movements over time to detect rhythm irregularities or sudden drops in activity.
- Comparison: While the CNN-LSTM model offers theoretically higher sensitivity for complex temporal patterns, it is computationally heavier. The Random Forest model was favored for this specific implementation due to its ability to maintain stable FPS on standard hardware without needing high-end GPUs.

3) One-Class SVM (Anomaly Detection) A One-Class Support Vector Machine (SVM) was evaluated for its capability in anomaly detection.

- Findings: While effective for detecting undefined abnormal events, SVMs can be sensitive to noise. The project mitigated this by implementing a decision logic engine that confirms persistence over time before triggering an alert, ensuring that momentary glitches do not cause false positives.

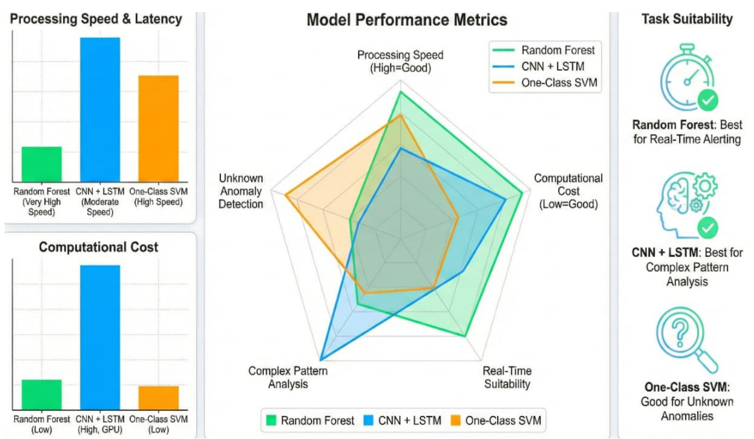

Fig. 1. comparison between different machine learning models.

B. Discussion of Findings

The results obtained from system testing and validation highlight several key findings regarding the effectiveness of AI-based non-invasive monitoring.

1) Real-Time Operational Stability The system successfully met the non-functional requirement of processing video at a stable frame rate, maintaining 20-30 FPS during continuous operation. The integration of MediaPipe for landmark extraction proved highly efficient, decoupling the inference speed from the camera resolution. This ensures that the system provides immediate feedback with a delay of less than 100ms, which is critical for emergency response.

Accuracy of Vision-Based Biomarkers The findings confirm that computer vision can effectively substitute physical sensors for detecting major cardiac events.

- Thoracic Movement: The system successfully utilized pose landmarks to monitor chest positioning and movement.
- Postural Collapse: The analysis of joint angles (shoulder-hip-knee) allowed the system to accurately detect sudden transitions from vertical (standing/sitting) to horizontal (lying) states, which is a primary indicator of cardiac arrest-induced collapse.

2) Efficacy of False Positive Reduction A significant finding was the importance of the Temporal Decision Logic Engine. During testing, raw frame-by-frame predictions occasionally fluctuated due to motion blur or lighting changes. By implementing a "persistence check" the system successfully filtered out these transient errors, achieving a "Pass" status in false negative tests. This logic ensures that alerts are only sent for genuine, sustained distress events.

3) Reliability of the Alert Mechanism The integration with the Twilio API was found to be highly reliable. In all valid test cases where an abnormality was simulated, the system successfully triggered the SMS alert workflow. The automation of this process eliminates the delay inherent in human observation, directly addressing the project's problem statement regarding unwitnessed cardiac events.
4) Privacy and Deployment The discussion highlights a major advantage of this "Edge Computing" approach. By processing coordinate data locally rather than transmitting video streams to a cloud server, the system preserves user privacy. This finding suggests that the system is suitable for deployment in sensitive home environments (e.g., bedrooms, bathrooms) where cameras are traditionally rejected, provided the video feed is not stored.

V. CONCLUSION

In summary, this investigation has successfully demonstrated the potential of machine learning enhancing the accuracy of cardiac arrest (CA) prediction utilizing heart health indicators. A primary finding of this research is the superior performance of the developed hybrid model which strategically leverages the strengths of thealgorithmsconfirming its effectiveness over alternative classification methods. This study affirms the utility of ML algorithms as a vital aid in the initial state diagnosis of cardiac arrest, which can subsequently inform and improve the timely administration of appropriate patient medications.While demonstrating clear utility, the research also identified specific opportunities for refinement in future work. To validate and expand the practical utility of these findings, future research should transition the analysis to real-world clinical datasets, thereby extending the applicability of the model beyond controlled test environments. techniques. By addressing these proposed steps, this research framework holds significant promise for contributing to life-saving diagnostics and ultimately reducing CA-related mortality rates.

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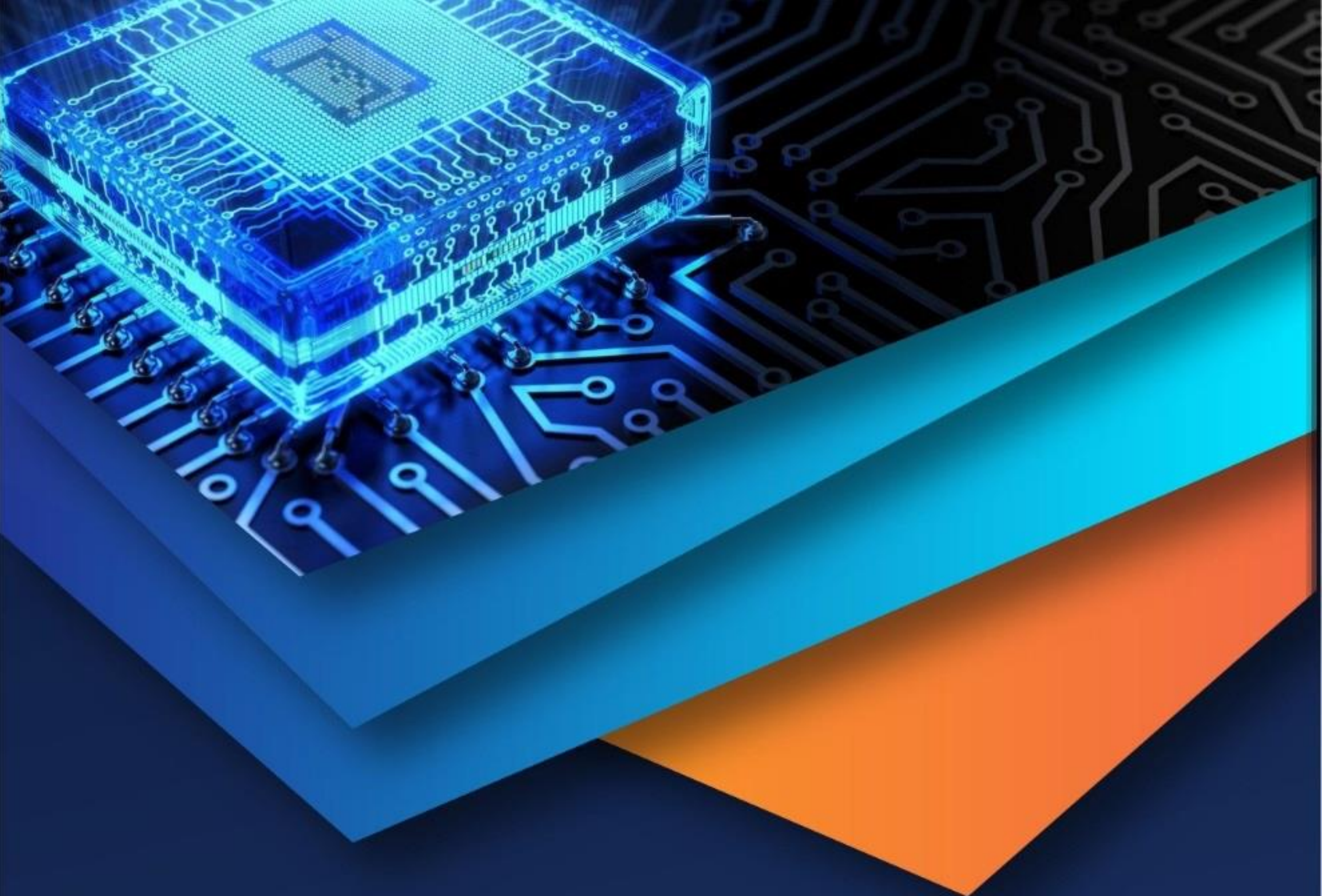

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