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Hand Gesture Recognition for Specially Impaired People Using IoT

Mr.Kancherla Balakrishna[1], P.Guru Manikanta[2], P.Phaneendra Kumar[3], P. Sai[4], P. Kavitha[5]
Dept. of CSE R.V.R. & J.C. College of Engineering Guntur, India

Abstract: Communication barriers faced by individuals with speech and hearing impairments limit effective interaction, especially in critical situations. This paper presents a real-time, standaloneembeddedIoT-basedhandgesturerecognitionsystem that operates without machine learning, reducing computational complexity and cost while improving portability. The systemuses a wearable glove equipped with five flex sensors to detect finger movements and an MPU6050 sensor to capture hand orientation, with processing handled by an ESP32 microcon- troller. A hysteresis-based threshold mapping technique encodes gestures using combined finger and orientation states, allowing multiple predefined gesture representations to be stored directly in memory. Experimental results from simulation and prototype testing demonstrate 96% accuracy with an average responsetime of 78 ms, satisfying real-time requirements and providing a practical, low-cost solution for assistive communication.
IndexTerms: HandGestureRecognition,IoT,ESP32, Flex Sensor, MPU6050, OLED Display, Assistive Technology, Threshold-Based Mapping, Hysteresis, PROGMEM, Sign Lan- guage, Embedded Systems.

I. INTRODUCTION

Communication is a fundamental component of human interaction. For individuals with speech and hearing impairments,however,thisprocesspresentssubstantialday- to-day challenges. These individuals rely primarily on sign language—a visual-gestural system of hand shapes, finger movements, and body postures—which is not widely under- stood by the general public, creating a persistent communica- tion barrier across social, medical, workplace, and emergency contexts.

Conventional solutions such as human sign language in- terpreters are expensive, unavailable on demand, and entirely impractical for continuous real-world use. Technological al- ternatives have emerged across two broad paradigms: *vision- based* systems, which use cameras and image processing pipelines,and*sensor-based*systems,whichinstrumentawear- ableglovewithflex sensorsandinertialmeasurementunits(IMUs).Vision-basedmore2022,murakami2021aresensitive to lighting conditions and background variation, and restrict the user to a camera's field of view. Sensor-based systemsthat use machine learning classifiers [4], [5] achieve broader gesture vocabularies but require significant RAM, labeled training datasets, and offline model inference, rendering them unsuitable for resource-constrained embedded platforms such as the ESP32 (520KB dynamic RAM).

This paper addresses these limitations through a determin- istic, threshold-based embedded approach that achieves O(1) gesture lookup complexity with no training data, no external hardware, and no wireless dependency. The key contributions are:

- A wearable glove integrating five flex sensors and an MPU6050IMUwithanESP32microcontrollerforreal- time gesture recognition without machine learning.
- A hysteresis-based dual-threshold mechanism that pre- vents signal flickering, ensuring stable gesture output.
- A PROGMEMflash indexing scheme supporting 192 gesture-orientation message combinations while con- suming zero dynamic RAM for the message table.
- Experimental validation achieving 96% recognition ac- curacywith 78ms average latency on a physical ESP32 prototype.

A. Overview of Problem Area

Individuals with speech and hearing impairments face sig- nificant challenges in communicating with people who do not understand sign language. Interpreter-based solutions are un- availableon demand andimpractical forcontinuous use.Most existing gesture recognition systems either rely on vision- based methods sensitive to environmental conditions, or on machine learning systems requiring external hardware and traininginfrastructure. Asimple, real-time,self-contained em- beddedsolutionforwearablegesture-to-textcommunicationis therefore needed.

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B. Solution and Outline

The proposed system uses a sensor-driven wearable glove with five flex sensors to detect individual finger bending and an MPU6050 IMU to classify hand orientation. These inputs are processed entirely on the ESP32, where a static threshold- based algorithm maps sensor readings to predefined sentences stored in flash memory. The matched sentence is displayed instantlyonanOLEDdisplay.Thisdesigneliminatescamera- based processing, external processing units, wireless depen- dency, and machine learning for a fixed gesture vocabulary.

C. Applications

The system addresses several practical assistive communi- cation scenarios:

- Healthcare Communication: Patients convey clinical needs to medical staff without interpreter dependency.
- Daily Communication: Expression of basic needs and emergency messages through predefined gestures.
- Workplace Inclusion: Enabling participation in profes- sional environments through gesture-based communica- tion.
- Educational Support: Learning aid for gesture-based interaction skills.
- Human-Computer Interaction: Gesture interface for triggering predefined IoT device actions.

II. LITERATURE REVIEW

Hand gesture recognition for assistive communication has been studied across both vision-based and sensor-based paradigms. Sensor-based approaches are generally preferred forwearabledeploymentowingtorobustnesstoenvironmental variation.

Shroke et al. [2] proposed a glove-based system for deaf- mute individuals using five bending sensors, touch sensors, and accelerometers. Gesture interpretation was performed on an ARM processor by comparing inputs against predefined voltage thresholds in memory—an architecture conceptually aligned with the present work, though lacking hysteresis, multi-orientation vocabulary expansion, and flash memory optimization.

Patel et al. [4] demonstrated gesture classification using ac- celerometerdataandmachinelearningclassifiers,establishing a benchmark for ML-based approaches. Kadam and Joshi [5] extendedthesensorapproachbyfusingaccelerometerandflex sensor data with pattern recognition, improving accuracy for complex static and dynamic gestures.

Lee and Lee [6] presented a wearable integrating five flex sensors, two pressure sensors, and a three-axis IMU with an Android text-to-speech application. Sankar and Hnat [7] de- veloped a real-time accelerometer-based system emphasizing cost-effectiveness and low computational overhead.

TABLEI:ComparisonofExistingGestureRecognitionAp- proaches

Reference	Sensors	Processing	Portab.	Cost
Shroke[2]	Flex+Accel	ARM Thresh.	High	Low
Patel[4]	Accel	ML Classif.	Medium	Medium
Lee & Lee[6]	Flex+IMU	AndroidApp	Medium	High
Murakami[?]	Camera	RNN(ML)	Low	High
More[?]	Camera	ImageProc.	Low	Medium
Proposed	Flex+IMU	ESP32 Thresh.	V.High	V.Low

III. METHODOLOGY

A. Existing System Analysis

An existing system referenced for comparison is the "Hand Gesture Vocaliser using IoT," which employs a glove-based design with flex sensors and a microcontroller. Captured gesturedataistransmittedwirelesslytoanexternalcomputing device where machine learning algorithms interpret gestures and produce voice output.

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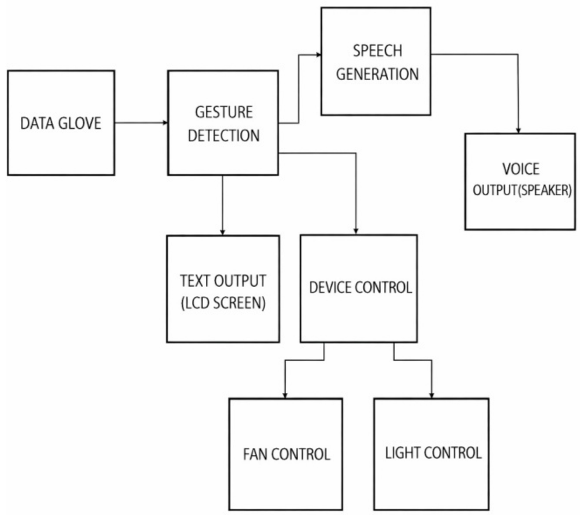

Fig.1:Schematicdiagramoftheexisting“HandGesture Vocaliser using IoT” System.

B. Proposed System

The proposed system eliminates all five limitations through a fully self-contained embedded design. Five flex sensors measure finger bending; the MPU6050 captures three-axis acceleration to classify hand orientation. Both streams are processed entirely by the ESP32, which executes a static threshold mapping algorithm and displays the matched pre- defined message on the OLED.

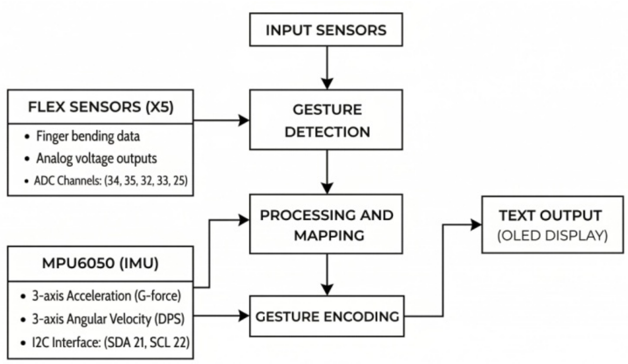

Fig.2:ProposedSystem”HandGestureusingIoTSystem”

Thissystemexhibitsfivecriticallimitations:

- MachinelearninginferencerequiressubstantialRAM and labeled training data.
- Wirelesscommunicationintroduceslatencyandconnec- tivity dependency.
- Externalprocessingunitsreduceportability.
- Multi-moduleintegrationsubstantiallyincreasescompo- nent cost.
- Higherpowerconsumptionisunsuitableforbattery- powered wearable deployment.

C. Algorithm

Algorithm1Real-TimeGestureRecognitionandDisplay

Input:FlexsensorADCvalues$\{P_1,\ldots,P_5\}\in[0,4095]$; MPU6050 acceleration $\{a_x, a_y, a_z\}$

Output:RecognizedgesturesentenceonOLEDdisplay

1:InitializeESP32,flexsensors,MPU6050,andOLED display

2:Average$N$ADCsamplesperflexchannel(moving-average filter)
3:foreachfinger$i \in \{1,\ldots,5\}$do
4: if$P_i \geq$POT_ON_THRESHOLD[i]then
5: fingerActive[i]$\leftarrow$true
6: elseif$P_i \leq$POT_OFF_THRESHOLD[i]then
7: fingerActive[i]$\leftarrow$false
8: endif
9:endfor
10:$G \leftarrow \sum_{i=0}^{4}$ fingerActive[i]$\times 2^i$,$G \in \{0,\ldots,31\}$
11:Apply100msstabilitytimer;hold$G$untilstable
12:Read$\{a_x,a_y,a_z\}$fromMPU6050viaI^2C
13:$B \leftarrow$dominantaxisindexwithsign;$B \in \{0,\ldots,5\}$
14:Apply300msstabilitytimertoconfirm$B$
15:$M \leftarrow$ PROGMEM_TABLE[B][G]
16:if$M \neq$currentdisplaymessagethen
17: UpdateOLEDwith$M$
18:endif
19:gotoStep2

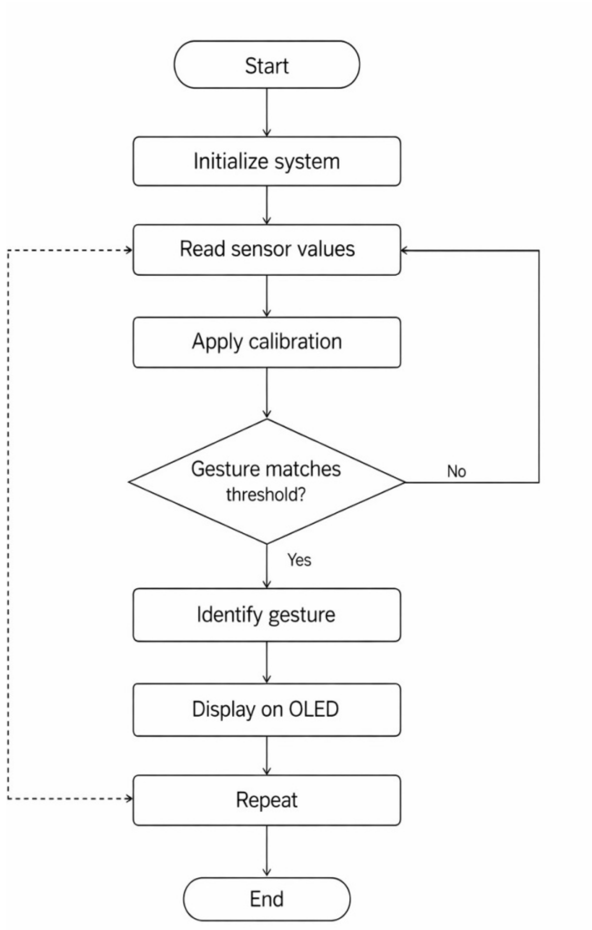

Fig.3:FlowchartoftheProposedSystem

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IV. SYSTEM DESIGN

The proposed system is organized into three functional modules.

Module 1 – Gesture Detection Module: Five flex sensors produceanalogvoltagesonESP32ADCpins(34,35,32, 33,25)proportionaltofingerflexion.TheMPU6050provides continuous 3-axis acceleration data via I^2C (SDA pin 21, SCL pin 22).

Module2–ProcessingandMappingModule:TheESP32appliesper-fingerhysteresisthresholdingtoproducea5-bitgestureidentifie r$G \in \{0,...,31\}$.Thedominantgravityaxis classifieshandorientationintobase$B \in \{0,...,5\}$.Thepair (B,G) indexes a 6 × 32 PROGMEM lookup table of 192 predefined messages.

Module 3 – Output Display Module: The matched mes- sage $M$is rendered on the OLED. The header line displays diagnostic values (B and G); the body line displays the full communication sentence. Refresh is event-driven.

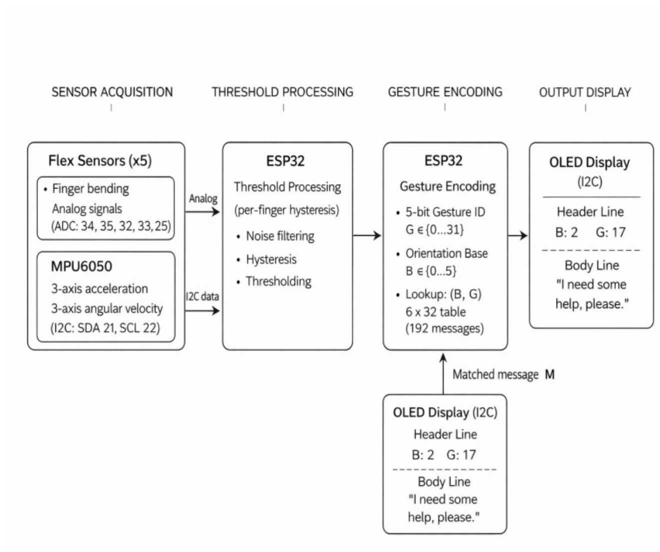

Fig. 4: Block diagram of the Proposed System illustrating the complete sensor acquisition.

V. IMPLEMENTATION

The hardware prototype consists of a wearable glove with five flex sensors routed to ESP32 analog input pins through individual voltage divider circuits. The MPU6050 and OLED display share the ESP32 I^2C bus.

Fig.5:Wokwisimulation:fivepotentiometersonESP32ADC pins (34, 35, 32, 33, 25) substitute for flex sensors; MPU6050 and OLED connected via shared I^2C bus.

Theimplementationfollowseightsequentialsteps:

1) Hardware Setup: Connect five flex sensors to ESP32 ADC pins; MPU6050 and OLED to the I^2C bus.
2) Software Configuration: Install Adafruit_SSD1306, Adafruit_MPU6050, andWirelibraries.
3) SensorCalibration:Determineper-finger POT_ON_THRESHOLDandPOT_OFF_THRESHOLD valuesempirically.
4) GestureRecognition:Implementhysteresisthreshold loop, 5-bit encoding, and 100ms stability filter.
5) Orientation Detection:Implementdominant-axiscom- parison and 300ms base stabilization timer.
6) PROGMEMTable:Define6×32messagearraywith PROGMEMattribute.
7) DisplayIntegration:Implementevent-drivenOLED update with header diagnostics and message body.
8) ThresholdRefinement:Validategesturerecognition and adjust thresholds to resolve ambiguous cases.

VI. RESULTS

A. Experimental Setup

Evaluation was conducted over 20 trials per gesture across five representative gestures plus the default (no-gesture) state, totalling 100 trials. Response latency was measured as the elapsed time between sensor value stabilization and OLED display update.

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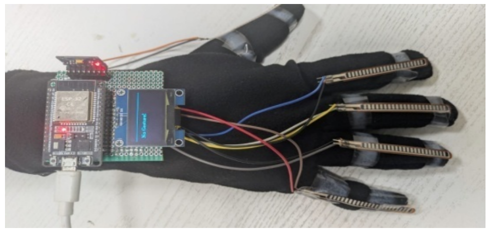

Fig. 6: Default State – No Gesture Detected: OLED displays no message; all five flex sensors below activation threshold.

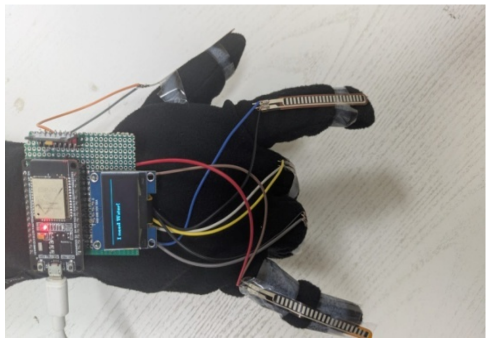

Fig. 7: Gesture : “Need Water” – recognized via specific 5-bit finger combination with hand in base-0 orientation.

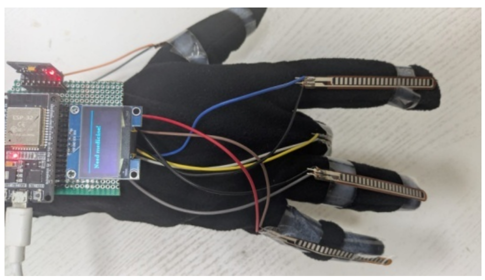

Fig. 8: Gesture : “Need Medicine” – distinct finger combina- tion demonstrating intra-base gesture discrimination.

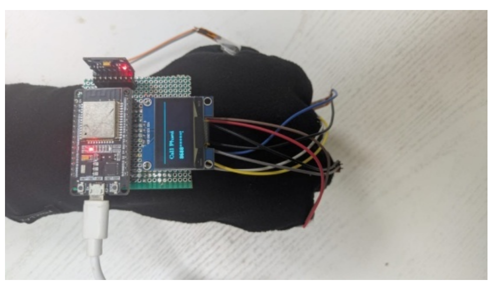

Fig.9:Gesture:“Emergency!Call”–highlydiscriminable threshold profile, achieving 100% recognition accuracy.

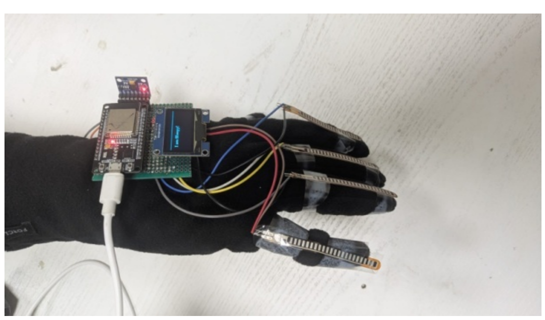

Fig. 10: Gesture 4: “I am Sleepy!” – highest latency (91ms) duetothresholdproximity;resolvableviaper-user calibration.

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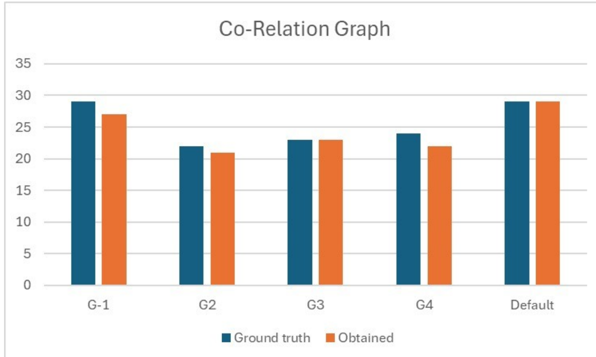

Fig.11:Co-RelationGraph

TABLE II: Gesture Recognition Accuracy and Response La- tency

Gesture	Trials	Correct	Acc.(%)	Latency(ms)
NeedWater(G1)	29	27	95.0	78
NeedMedicine(G2)	22	21	95.0	82
EmergencyCall(G3)	23	23	100.0	74
IamSleepy!(G4)	24	22	90.0	91
NoGesture(Default)	29	29	100.0	65
Overall	127	122	96.0	78(avg)

TABLEIII:PerformanceComparisonwithExistingSystems

System	Accuracy(%)	Latency(ms)	Ext.HW
Pateletal.[4](ML)	~92	~200	Yes
Lee&Lee[6](Android)	~95	~300	Yes
Shrokeetal.[2](Thresh.)	~88	~120	No
Proposed(Threshold)	96	78	No

Keyobservationsfromtheevaluation:

- Hysteresis-based dual-threshold detection eliminated false-trigger events observed in single-threshold testing.
- PROGMEMstorage reduced dynamic RAM consumption for the message table to zero, enabling stable firmware operation.
- MPU6050 dominant-axis orientation classification was correct across all tested orientations, validating the 3D- aware strategy.
- Event-driven OLED update produced flicker-free output across all gesture transitions.

VII. CONCLUSION

This paper presented a real-time, standalone embedded gesture recognition system for individuals with speech and hearing impairments. The primary contribution is a low-cost IoT wearable achieving deterministic gesture-to-text commu- nication across 192 unique gesture-orientation combinations, without dependency on machine learning, wireless communi- cation, or external computing hardware.

Threecoredesigndecisionsjointlyenablereliable,real-time operation within the ESP32's resource constraints: hysteresis- based dual-threshold flex sensor detection for flicker-free fin- ger state classification; MPU6050 dominant-axis gravity pro- jection for 3D-aware orientation classification; and PROGMEM flash indexing for zero-RAM-cost message storage. These yield O(1) gesture lookup with deterministic sub-100ms la- tency.

Experimental evaluation demonstrated 96% overall recog- nition accuracy with a 78ms average response latency across 100testtrials,validatedonbothasimulationplatformand a physical prototype. Future work will prioritize per-user calibration,text-to-speechoutput,IoTconnectivityviaMQTT, and expanded gesture vocabulary validation.

VIII. FUTURE SCOPE

A. Short-TermEnhancements:

1) Per-UserCalibrationMode:Startupcalibrationroutine for personalized threshold values per user.

2) Text-to-SpeechIntegration:AddaDFPlayerMinior DFRobot TTS module for audible speech output.
3) Battery-Powered Wearable: LiPo cell with deep-sleep power management for untethered daily use.
4) ExpandedVocabularyTesting:Validatealargersubset of the 192 supported combinations.

B. Long-TermEnhancements:
1) IoT Connectivity via MQTT: Transmit recognized messagesoverWi-FiusingtheESP32'sbuilt-inwireless interface.
2) Machine Learning Integration: Lightweight Tensor- Flow Lite model for adaptive recognition beyond fixed sets.
3) Multi-Language Sign Language Support: Extend PROGMEM table to support ASL, ISL, and BSL.
4) SmartHomeIntegration:Gesture-basedIoTdevice control via Amazon Alexa or Google Home.
5) Emergency Alert System: GPS and GSM modules for location-stamped emergency alerts.

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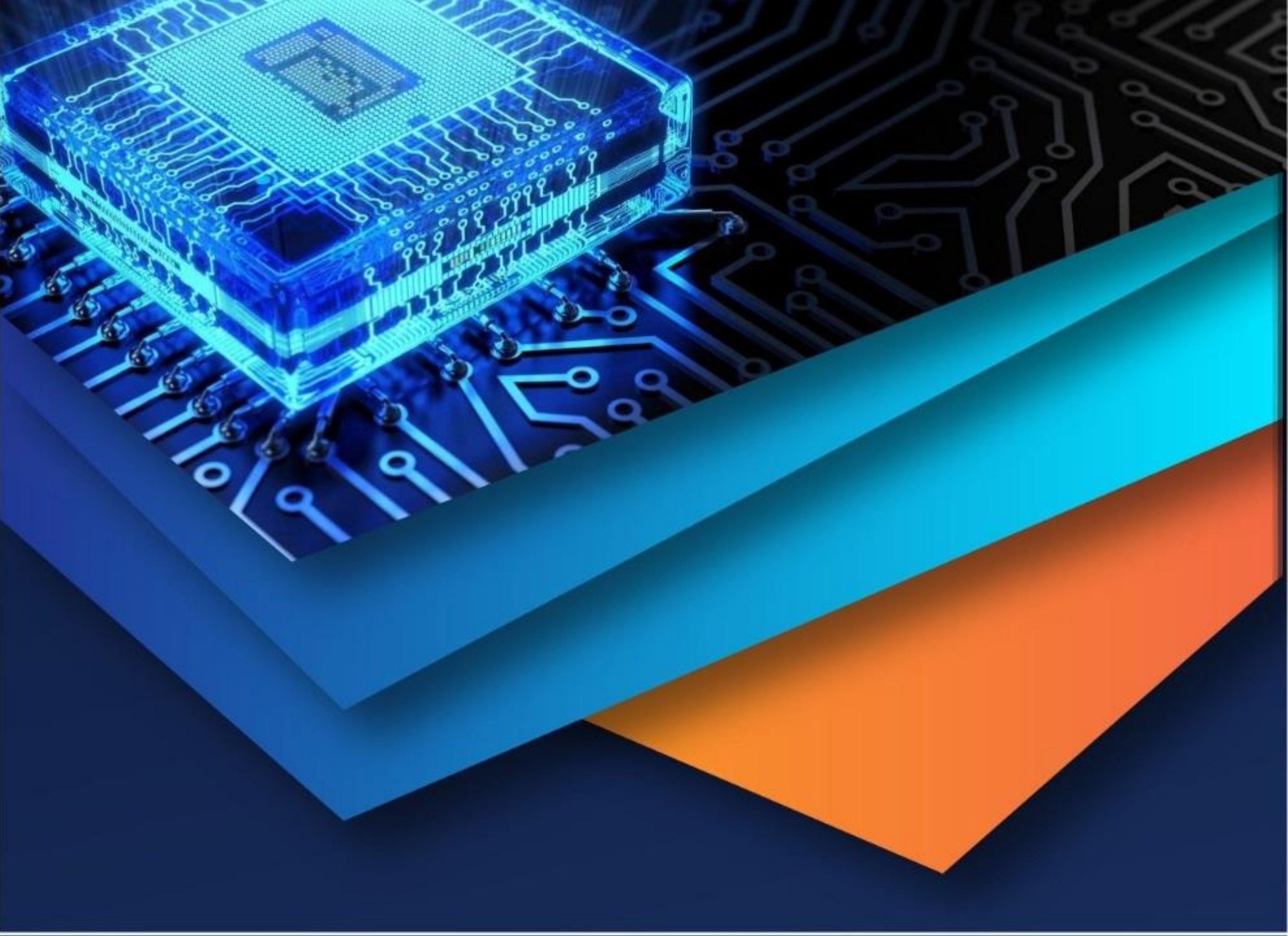

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