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Real Time Risk Prediction of heart patients using HRV and IoT: A Survey

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Abstract: In today's world, the leading cause of death is heart disease. The term heart disease is described as several different conditions that affect the heart. There are many types of heart disease, but the most common are coronary heart disease, congestive heart failure, and arrhythmia. Currently, the healthcare system is hospital essential which is inefficient to treatthese conditions, which require immediate assistance. This is a roundabout way to point to a rise in the death rates. Heart rate variability (HRV) is a useful tool for identifying and monitoring potential risk factors for heart disease. HRV measures the time between each heartbeat and can be used to identify subtle changes in heart rate that may be indicative of an underlying health condition. With the help of Machine learning and (Internet of Things) IoT-based heart patients real-time monitoring and predicting risk analysis will enable doctors to view patient's health status online. Internet of Things (IoT) technology to continuously track and monitor vital signs,including heart rate, pulse rate, and body temperature. In addition to these traditional vital signs, the system also includes afeature for monitoring heart rate variability (HRV), which has been shown to be a useful indicator of heart disease risk prediction. Using machine learning and HRV capabilities, the system will be able to assess health status and anticipate patient'sheart health (low-risk or high-risk) based on the ECG waveform and HRV characteristics such as time domain and frequency domain values

Keywords: Heart disease, Heart rate variability, Real time Monitoring, Prediction, Machine learning, Internet of things.

I. INTRODUCTION

Heart disease, refer as cardiovascular disease, it is a group of circumstances that affect the heart and blood vessels.These conditions can include coronary artery disease (CAD), heart failure, heart valve problems, and abnormal heart rhythms (arrhythmias). Heart disease is the leading cause of death worldwide, and it can occur at any age. Coronary artery disease (CAD) is the most common form of heart disease and occurs when the arteries that supply blood to the heart becomenarrowed or blocked. Heart failure is a condition in which the heart is unable to pump enough blood to meet the body's needs. This can lead to symptoms such as shortness of breath, fatigue, and swelling in the legs and ankles. Heart valve problems occur when the heart's valves, which regulate the flow of blood through the heart, do not function properly. Thiscan lead to problems such as leaky valves (regurgitation) or narrowed valves (stenosis). Arrhythmias are abnormal heart rhythms that can cause the heart to beat too fast, too slow, or irregularly. These can range from mild and benign to severe and life-threatening. There are several risk factors for heart disease, including high blood pressure, high cholesterol,diabetes, obesity, smoking, and a family history of heart disease. Many of these risk factors can be managed ormodified through lifestyle changes, such as eating a healthydiet, getting regular exercise, and not smoking. Early diagnosis and treatment of heart disease can help prevent thedevelopment of more serious health conditions and improvethe chances of a full recovery.There are several different typesof heart disease, including:Coronary artery disease (CAD),Heart failure, Heart valve problems, Abnormal heart rhythms (arrhythmias), Cardiomyopathy, Congenital heart disease, and Heart infection. Overall, the types of heart disease can rangefrom mild to severe and can have a significant impact on aperson's health and quality of life. Early diagnosis andtreatment of heart disease can help prevent the development ofmore serious health conditions and improve the chances of afull recovery. HRV (heart rate variability) may be a usefultool for assessing and managing the risk of heart disease, butit is not a direct solution to heart disease itself. Heart ratevariability (HRV) is a measure of the fluctuation in the time interval between successive heartbeats. It can be used as a marker of cardiac health and has been suggested as a potentialtool for the early detection and prevention of heart disease.Rather, HRV is a measure of the variations in the time intervalbetween successive heartbeats, and it is thought to be a usefulindicator of the health of the autonomic nervous system. Bymeasuring HRV, it may be possible to identify individualswho are at an increased risk of developing heart disease andtake steps to manage that risk. There are several factors thatcan influence HRV, including age, gender, physical activity levels, and stress. It is thought that HRV may be influenced bythe balance between the sympathetic (arousing) and parasympatheticc (relaxing) branches of the autonomic nervoussystem.

A. Problem Formulation

Limited access to medical data: Access to medical data is limited due to privacy laws and regulations. This makes it difficult for researchers to collect large datasets for analysis.

1) Lack of integration of data sources: Most existing heart disease risk prediction systems rely on data from a single source, such as EHRs. This limits the accuracy of predictions since the data is not from multiple sources.
2) Insufficient patient data: Data from patients is often not available in sufficient quantities, making it difficult to accurately predict risk.
3) Lack of patient engagement: Patient engagement is often low, making it difficult to collect data from them in order to make accurate predictions.

The Present work overcomes these difficulties , As we have used Combination of IOT and Machine Learning Algorithms in our Project. By leveraging the power of machine learning and HRV, the project will be able to assess health status and predict patient's heart health (low-risk or high-risk) based on the ECG waveform and HRV factors like time domain and frequency domain values. In this project, we are using components Arduino Uno, NodeMCU, and sensors such as a Temperature sensor (DS18B20 Waterproof sensor probe), Pulse sensor, and AD8232 ECG sensor, And we also use ML to do an analysis of a patient's heart health. In IOT part, the sensors such as Temperature sensor (DS18B20 Waterproof sensor probe), Pulse sensor, and AD8232 ECG sensor are used to collect Temperature , Pulse and ECG Data Respectively from the patients. Then we apply ML algorithmson the collected data to perform analysis and check the accuracy of the model. Here we have used Linear regression Algorithm to predict the accuracy.

B. Linear Regression

Linear regression is a supervised machine learning approach that uses one or more input variables to predict a continuous numerical output. It is a linear way to modelling the connection between one or more independent variables and a dependent variable. The linear regression technique presupposes that the input and output variables havea linear connection, which means that the output is a linear combination of the input variables.

II. LITERATURE SURVEY

The purpose of this study is to explain the principles of constructing a real-time HRV biofeedback system employing deep breathing exercises by investigating the shortest time frame of RR intervals that results in a credible analysis. It looks into the suitable HRV measurements by assessing the major differences between resting and breathing situations, as well as the consistency of trends throughout ultra-short-term segments. Overall, the results indicate that a 20-second time frame can offer a credible HRV time-domain analysis. SDNN,LF, and total power are examples of HRV metrics that may beutilized in a real-time biofeedback system. These findings willhelp to shape the design of a multi-modal self-monitoring HRV biofeedback system.[2]

HRV is strongly recognized in seizures; it represents autonomous nervous system disruption and can give important clinical information that can be utilized to detect seizures. Electroencephalography (EEG) was the first instrument used to monitor brain activity and seizures for decades. However, employing EEG is impractical since it requires attaching electrodes to the scalp of the head, it takes time to obtain data,and it is often utilized while or after seizures occur. In this project, we want to develop an epileptic seizure detectionsystem based on heart rate monitoring and the internet of things (IoT). The sensor utilized is a pulse sensor, which is employed as a heart rate detector processed by NodeMCU. The test results and measurements will be shown on LCD in real-time and communicated to the ThingSpeak platform, where physicians and family members may track the patient's state.[9]

This work describes an ultra-low power ECG platform for continuous and less invasive monitoring of systems with limited processing capabilities. By collecting and analyzing information related to distinct cardiac patterns, the platform is capable of identifying anomalies in the ECG data.

The platform is designed to function continuously on either of the 12 leads, and the work presented includes a single lead implementation that operates on lead I or II. A single-lead, wearable ECG patch has been created that can identify rhythm-based arrhythmias as well as constantly monitor beat- to-beat heart rate and breathing rate.[10]

The electrical activity of the heart is represented by an electrocardiogram (ECG), which may be used to examine cardiac health. Subtle alterations in the ECG's P-QRS-T wave are frequently used to portray a specific type of cardiac problem. In this paper, we used heart rate (derived from ECG) as the basic signal for our analysis to show how well we can distinguish cardiac rhythm problems. The typical heart rate ranges from 60 to 100 beats per minute.

These signals are extremely nonlinear and nonstationary. In this study, we looked at 352 people from nine distinct cardiac groups. As a result, we employed nonlinear entropies as characteristics of these heart rate signals.[14]

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Sudden Cardiac Death (SCD) is defined as an unexpected death followed by Ventricular Fibrillation (VF) or Ventricular Tachycardia (VT), which is often identified using an electrocardiogram (ECG).

Predicting the development of SCD is critical for speedy treatment and, as a result, lowering the death rate. We propose an automated prediction of SCD utilizing Recurrence Quantification Analysis (RQA) and Kolmogorov complexity factors taken from Heart Rate Variability (HRV) data in this research. The collected characteristics are submitted to k-Nearest Neighbor (k-NN), Decision Tree (DT), Support Vector Machine (SVM), and Probabilistic Neural Network (PNN) classifiers for automatic categorization of normal and SCD classes for periods of 1min,2min, 3min, and 4min before SCD. Our findings reveal that we can predict SCD four minutes before it occurs with an average accuracy of 86.8%, sensitivity of 80%, and specificityof 94.4% using the k-NN classifier and an average accuracy of86.8%, sensitivity of 85%, and specificity of 88.8% using the PNN classifier.[18]

III. PROPOSED SYSTEM

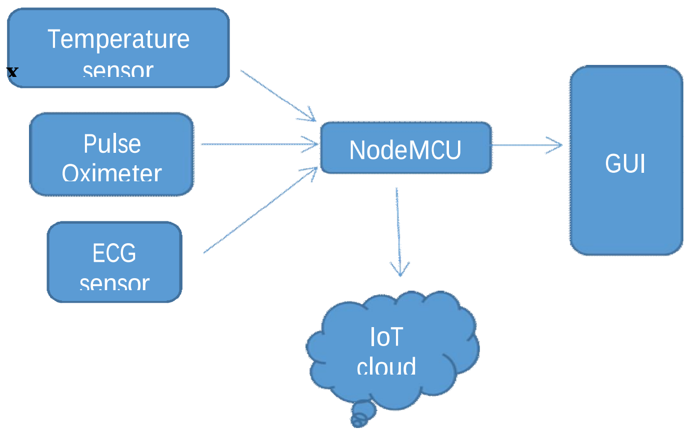

Fig. 1 Block diagram of real time risk prediction of heart patients using HRV and IoT

According to the figure above, we are employing three sensors: temperature, pulse oximeter, and ECG. The temperature and pulse oximeter data are sent to Arduino and then to the ThingSpeak server, an IoT cloud platform. The NodeMCU is used to transport data from Ardiuno to the IoT cloud. In the instance of an ECG sensor, because we require real-time monitoring and prediction of HRV, the ECG data is sent to Arduino for analysis. Finally, the findings from all of the sensors are shown in the system's graphical user interface.

Thingspeak server: ThingSpeak is a cloud-based IoT platform that allows users to gather, store, and analyse sensor data. It enables users to establish "channels" to represent various sensors or devices, and then use the ThingSpeak API to communicate data to those channels. The platform alsoprovides visualisation tools such as graphs and maps to assist users in comprehending the data being collected. ThingSpeak also allows users to set up alerts and triggers depending on data, and it can interface with other apps and services via its API.

IV. SYSTEM PROCESSING

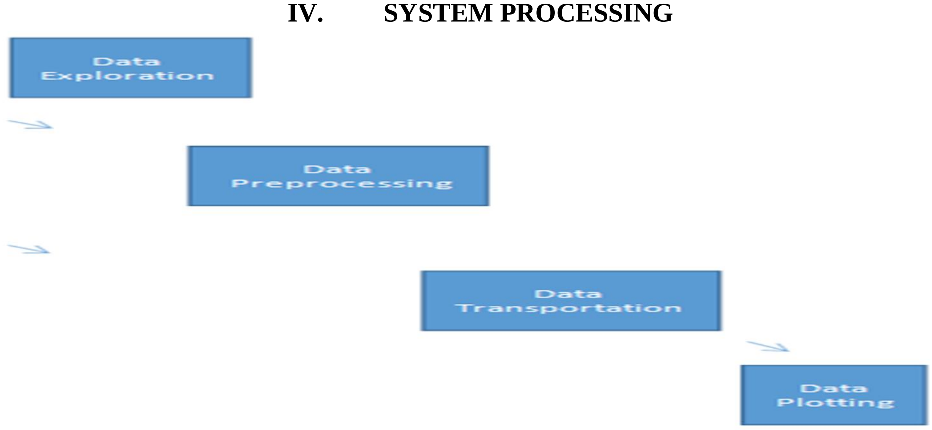

Fig. 2 Python GUI Stages

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The system is categorised into 2 components, viz. Hardware & Software; while hardware unit comprises of transmitter portion and receiver section and software package unit consists of software package language like python. Data exploration is the act of comprehending and studying a datasetin order to obtain insights and identify patterns. It can assist inidentifying patterns, outliers, and possible data concerns. Real-time risk prediction of cardiac patients combining HRV and IoT entails monitoring a patient's heart activity using sensor data acquired through wearable devices. Data preparation is the process of cleaning and modifying data to prepare it for analysis. It has the potential to greatly enhance data quality and make it easier to evaluate. Data transportationrefers to the process of transporting data from one location to another, whether inside an organisation or across organisations. Data plotting is the process of visualising datain the form of graphs or charts. It is a key stage in data exploration and analysis since it may aid in identifyingpatterns and trends in data and making it simpler to interpret.

V. DIFFERENT COMPONENTS FOR PROPOSEDSYSTEM

A. DS18B20 Waterproof Temperature Sensor

Fig. 3 DS18B20 Waterproof Temperature Sensor

The Dallas semiconductor and maxim integrated businesses make a waterproof version of the DS18B20 waterproof temperature sensor, which is a pre-wired, one-meter-long, sealed, waterproof digital temperature sensor probe. It is simple to use, well-designed, and convenient for measuring temperature in a variety of environments. The integrated digital-to-analog converter produces a 1-wire digital temperature sensor with a precision of 12 bits. Its operation is based on the direct transfer of temperature to digital format and runs in parasitic power mode. This sensor operates on a 1-wire serial communication protocol and saves a 64-bit unique serial code. Because this is a 1-wire digital temperature sensor, it just requires the data and GND pins to communicate with the Arduino or microcontroller. The sensor's temperature detection range is -55°C to +125°C witha 5°C precision. It is the greatest temperature sensor for measuring the temperature at various sites, and it only requires one data/digital pin of the Arduino or microcontroller unit to convey data. It requires a positive power source of 3V to 5.5V and uses a maximum current of 1mA. The major benefit of the DS18B20 is its alarm feature. When the temperature measurements hit a high or low threshold value defined by the user, the output signal can be preset.
Pin 1 (Ground): This pin is used to attach to the circuit's GNDterminal.
Pin2 (Vcc): This pin is used to supply the sensor with power,which might be in the range of 3.3V or 5V.
Pin 3 (Data): This pin provides the temperature value and isused for 1-wire communication.

B. Pulse Oximeter Sensor

Fig. 4 Pulse Oximeter Sensor

To detect blood oxygen saturation, pulse oximeter sensor employs a light-emitting diode and a receptor. The fraction of oxygen bound to haemoglobin in the blood is referred to as oxygen saturation. The deciding principle is based on the fact that oxygenated blood absorbs more infraredlight than deoxygenated blood. The pulse oximeter calculates the absorption of different wavelengths of light and displays the pulse rate and percentage of oxygen in the blood.

Pin Configurations:

VIN: This pin provides electricity to the sensor. This sensor operates at 3.3-5V.

SCL: This is a I2C serial clock pin.SDA: This is a I2C serial data pin.

INT: The active low interrupt pin is denoted by the symbol INT. The inbuilt resistor pulls it HIGH, but when an interrupt occurs, it drops to LOW until the interrupt clears.

IRD: Infrared LED Cathode with LED Driver Connector

RD: Red LED Cathode and LED Driver Connection Point GND: This pin is attached to the source ground pin and isused to deliver ground to this sensor.

C. AD8266 ECG Sensor

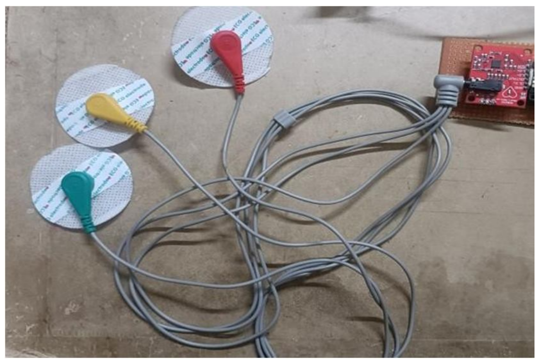

Fig. 5 AD8266 ECG Sensor

The AD8232 ECG sensor is a commercially available board that is used to determine the electrical movement of the human heart. This activity may be charted in the same way that an electrocardiogram is, with the output being an analog readout. Because electrocardiograms may be highly loud, the AD8232 chip can be used to minimize the noise. The ECG sensor operates similarly to an operational amplifier to obtaina clear signal from the intervals simply. The AD8232 sensor isutilized for biopotential measuring applications and signal conditioning in ECG. This chip's primary function is to amplify, retrieve, and filter biopotential signals that are weak in noisy environments such as those created by replacing a distant electrode and motion.

The pins SDN pin, LO+ pin, LO- pin, OUTPUT pin, 3.3V pin, and GND pin are part of the heart rate monitoring sensor like the AD8232. such that soldering pins will allow us to attach this IC to development boards like Arduino. Additionally, this board has connections for connecting custom sensors, such as the right arm (RA), left arm (LA), andright leg (RL) pins. This board uses an LED indicator todisplay the human cardiac rhythm. The AD8232 sensor has a feature called rapid restoration, which is utilized to shorten thelength of the HPFs' lengthy resolving tails. This sensor is available in a 4 mm x 4 mm dimension, and it comes in a 20-lead LFCSP package. It runs between 40°C to +85°C, while its performance is indicated between 0°C and 70°C.

D. NodeMCU

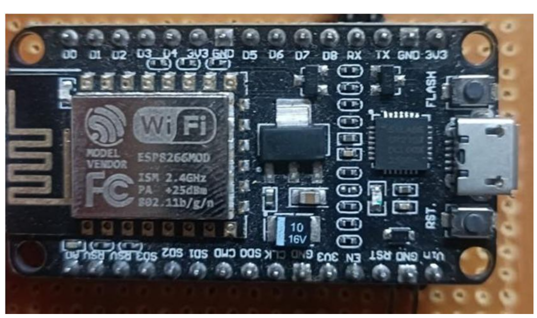

Fig. 6 NodeMCU

The Node MCU ESP8266 Wi-Fi module is a SOC microchip that is mostly used for developing end-point IoT (Internet of things) applications. It is referred to as a standalone wireless transceiver, and it is relatively inexpensive. It is used to link numerous embedded system applications to the internet.

Pin Configuration: The ESP8266-01 Wi-Fi module has two modes of operation. They are as follows:

When the GPIO-0 and GPIO-1 pins are active high, the module executes the software that was uploaded to it.

UART Mode: When GPIO-0 is active low and GPIO-1 is active high, the module enters programming mode and may becontrolled through serial connection via an Arduino board.

VI. CONCLUSION

There were preceding IOT-based projects for Heart Rate Variability (HRV) and some Machine Learning (ML)-based projects for HRV. However, we use and utilize the Internet OfThings (IoT) and ML for HRV to forecast the risk of cardiac patients in real time. Using machine learning and HRV potentialities, the project can estimate health status and anticipate patients' heart health (low-risk or high-risk) based on the ECG waveform and HRV characteristics such as time domain and frequency domain values. In Machine Learning, we employed the Convolutional Neural Network approach to identify the stages of Hearth Risk.

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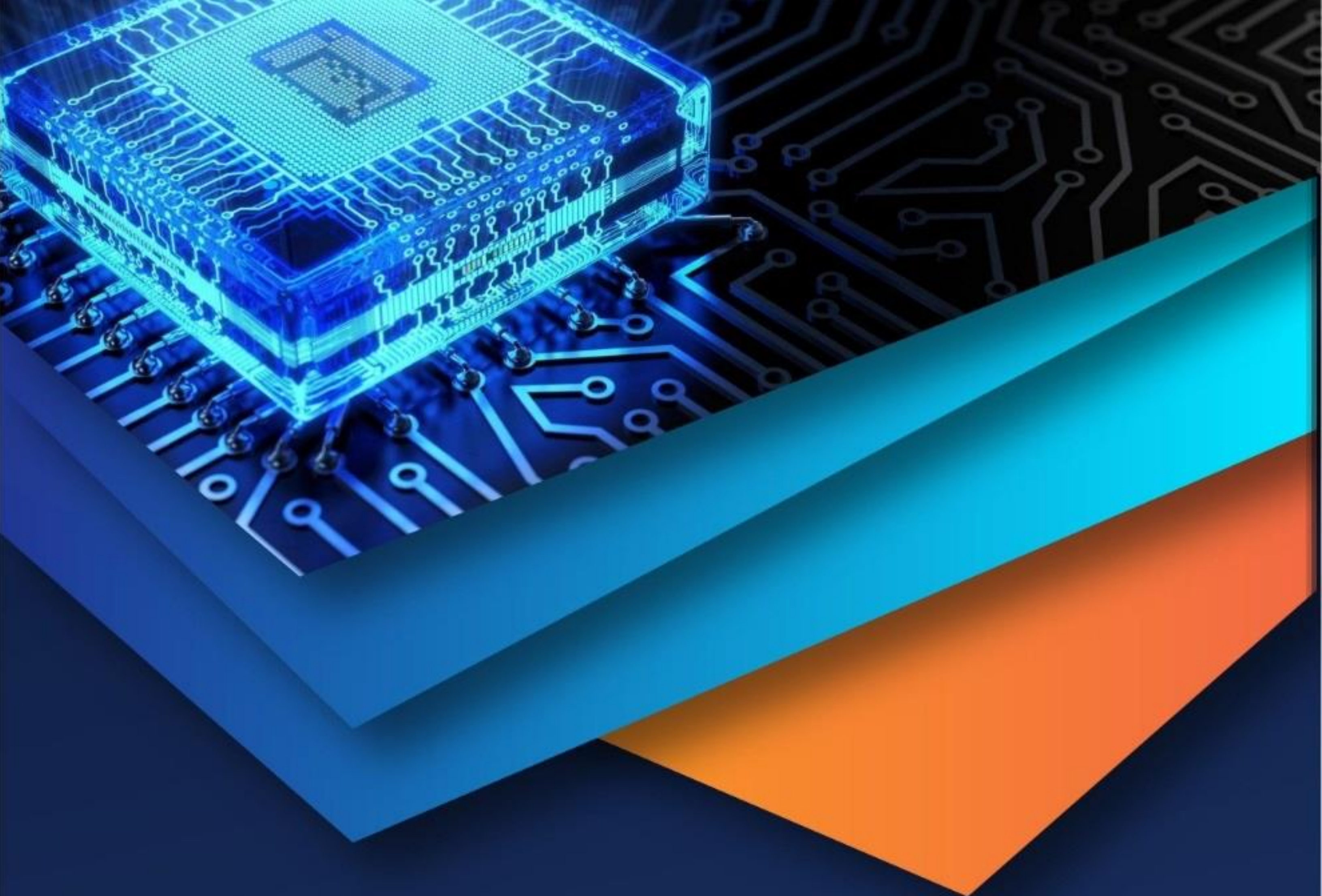

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