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Live Health Monitoring System

Chellannagari Bhuvana[1], Lavanya Allaparthi[2], Galipalli Harshitha[3], G. Indu[4]
Dept. of CSE (DATA SCIENCE), Institute of Aeronautical Engineering, Hyderabad, India

Abstract: The Live Health Monitoring System predicts the health issues in patients using a machine learning algorithm that was trained on actual health data. After health data is inputted by the user, the system processes and provides an instant prediction of the risk (high or low). The most important health factors which it mostly checks are the heart rate, body temperature, breathing rate, systolic and diastolic blood pressure, and SPO2 levels. In order to offer a user-friendly and interactive interface, HTML, CSS and JavaScript have been used in creating the front end of the site. Python framework was built on the back end, and the machine learning model was incorporated and the data preprocessed with the help of Python modules. The key objectives of the platform are to help track the health condition of a patient in real-time and reduce the use of manual checks. This technique improves convenience and preventive therapy to users and health practitioners because it allows early and distant identification of potential ailments. To implement suitable analysis of the trends in vital conditions and predict potential health risks, the machine learning model was trained on the healthcare dataset. After the user inputs their vitals and the learnt data of the model, the system gives a clear and classification of the risk result. The index phrases include health monitoring, machine learning, vital signs, real-time monitoring, health risk prediction, web application, remote healthcare, Python, data preprocessing, SPO2, and heart rate.

Index Terms: Health Monitoring, Machine Learning, Vital Signs, Health Risk Prediction, Real-Time Tracking, Web Application, Remote Healthcare, Python, Data Preprocessing, SPO2, Heart Rate.

I. INTRODUCTION

Introduction: he rising number of digital technologies being used to enhance patient care and monitoring has led to signif- icant changes in the healthcare sector over the last few years. One of such inventions is the Live Health Monitoring System that focuses on constant monitoring of the vital physiological factors such as heart rate, body temperature, oxygen saturation (SpO_2), respiration rate, and blood pressure. This will assist the caretakers and medical professionals in keeping up with the status of a patient and respond immediately when anomalies are detected remotely by enabling real-time data collection and processing. The program provides users with immediate access to health information via a web-based platform, enhancing the response time and efficacy of medical response in cases of emergency intervention. The user interface was developed using HTML, CSS and JavaScript to ensure usability and accessibility to device. The system is developed with Python on the server side, where the collected data is analyzed with the help of machine learning, namely, the Random Forest algorithm, to determine potential health issues. In this predictive approach, the focus is laid on the preventive and the early intervention rather than the postponed one.

Flexibility and expansion in the future are also considered as the system is constructed. The modular design allows it to be integrated with wearable technology and IoT-enabled medical devices and also add more indicators of health. Further features such as the monitoring of glucose level and the electrocardiogram (ECG) can be added in the update. The frontend is capable of accepting new parameters and does not necessitate any major structural changes, whereas, on the contrary, the backend architecture enables upgrades without any hassle.

Another important characteristic of the system is the ability to analyze patterns with time. By continually analyzing patient data, it will be able to notice minor variables in vital signs that may not be easily noticeable at first but may indicate under- lying conditions. This will enable fast medical response and enhance early warning measures. The system can be applied in cases when accuracy and consistency are essential because the random forest algorithm ensures reliable and precise forecasts. On the whole, Live Health Monitoring System contributes to the increased effectiveness, active character, and easy access of healthcare delivery.

A. Literature Survey

The online business environment is experiencing a surge in the use of digital technologies, and this trend is not expected to fade away soon. The healthcare industry has numerous networked entities. There is a tremendous industry change. It is the dire need of a digital revolution that is the main factor in this digital revolution. technologies related to conveniently accessible real-time health tracking, particularly after a societal health crisis such as the COVID-19 pandemic.

These systems have made it possible to have continuous care of patients. monitoring, encouraged preventative care, and decreasing hos- pitalization. The Live Health Monitoring System, which will be proposed within the framework of this research, as a seamless web-based system with an AI-driven capability to analyze the data in real time and evaluate the risks to the health of patients, is a step forward into this changing envi- ronment. These solutions have made continuous patient care a possibility. observation, decreased hospitalization and more preventive treatment. The Live Health Monitoring System that is proposed in this study builds on this changing environment by providing a smooth, AI-powered, web-based platform that can analyze data that is provided in time and assess the risk associated with patient health. In this section, the gaps that our system is intended to fill are highlighted and past research and recent progress are examined.

B. Existing Work In Health Monitoring Systems

IoT-based health monitoring systems: The ability to monitor patient health remotely has improved significantly, owing to the application of the Internet of Things (IoT) technology. Such systems may have sensors, microcontrollers, and com- munication devices such as Wi-Fi or Bluetooth to collect and transmit physiological data. The devices constructed on boards such as Arduino or Raspberry Pi are often used to measure vital parameters and transmit them to a cloud service, such as AWS, Google Cloud, or Microsoft Azure. Even though such solutions are effective in collecting continuous data, they often do not possess advanced analytical abilities particularly in areas that involve machine learning-guided forecasting to detect health threats.

Mobile Application-Based Monitoring: Mobile health appli- cations have become popular as a source of monitoring per- sonal wellness and fitness by the popularity of smart phones. Such applications as Fitbit, Google fit, Apple health, and Samsung health provide people with visual summaries of their activity, such as sleep habits and activity in steps and calories. These platforms are made to be simple to use and integrate with wearable technology. But instead of clinical observance, they continue to give significant attention to general fitness. As a rule, they do not provide real-time risk notifications, medically certified predictions, and support with a detailed health measurement, such as blood pressure and respiratory rate. They also offer restricted customisation to individuals who already have existing medical problems.

Health Prediction Systems, AI in Outpatient Environment: The recent developments in machine learning and artificial intelligence have proved to have great potential in medical diagnostics. Algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest have been applied to patient datasets to predict conditions such as oxygen shortage, diabetes, and heart diseases. Regardless of such developments, many of such models are designed in distant research settings and not integrated in real time systems. Due to this, they have yet to be utilized effectively in the continuous monitoring of patients.

Research Gap: Most systems however focus on either data collection and forecast analysis although they rarely bring the two together in the same platform, as an analysis of existing solutions attests. There is an apparent lack of systems that effectively integrate both interactive web-based interfaces to real-time monitoring and machine learning models. Existing systems currently have limited complete end-to-end archi- tectures connecting the frontend technology and predictive models of the backend. More so, embodied patient history or overtime patterns are often not customised in the ex- isting systems. Another major disadvantage is the absence of transparency in model forecasts, which lacks confidence in the user. The effectiveness of predictive models is also undermined by the fact that most existing datasets are rather narrow and cannot be able to predict a number of health factors simultaneously.

C. Requirements Specifications

The hardware and software resources are covered in this section. softwares needed to build and run the Live Health Monitoring System, on top of the basic functions that the system is expected to happen to have.

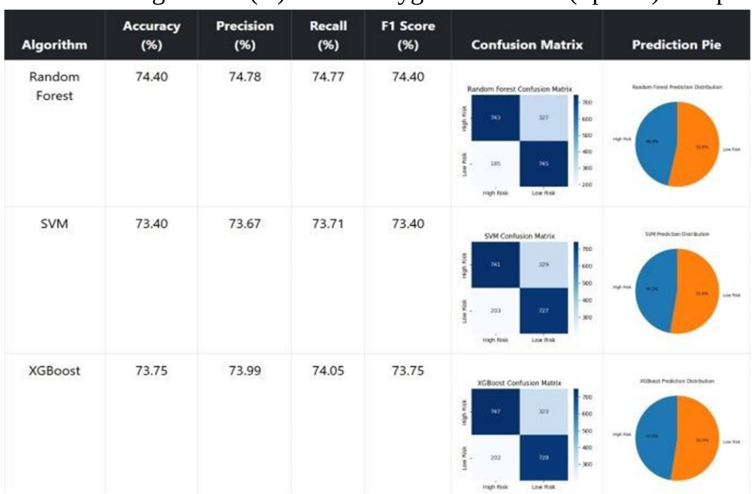
D. System Architecture

The smart web-based Live Health Monitoring System plat- form predicts health risks based on the real-time patient input through the mixture of machine learning and front-end devel- opment paired with the learning-based back-end. The system is developed on the existing web technology. technology and Python-powered backend framework that allows vital signs analysis and real-time projecting health status. The architec- ture is well planned in performance optimization. predictive accuracy and feasibility.These modules include a data input, data preparation, and user login module. processing, warning patients about high-risk people, visualizing results, database management, and predicting health concerns with the help of Random Forest. Collectively, these elements create the real- time monitoring of patient health and make a timely decision related to medical intervention.

All these crucial elements are required to make the Health Monitoring System to support intelligent decision-making and real-time monitoring of patients. The system begins with the user login. authentication module which provides patients, administrators and doctors with secure and role-based authentication. Observing After logging in, the Data Input Module collects patient health information. interconnected equipment variables (e.g. oxygen, body temperature, heart rate saturation, etc.) automatically or manually.

II. UNITS

All measurements in this live health monitoring system have been set to the International System of Units (SI) in order to be consistent and accurate. The heart rate is the number of beats per minute (bpm), and body temperature is the number of degrees Celsius (o C) with the equivalent SI unit being Kelvin (K). Blood oxygen saturation (SpO 2) is expressed in percentage.



Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Confusion Matrix	Prediction Pie
Random Forest	74.40	74.78	74.77	74.40		
SVM	73.40	73.67	73.71	73.40		
XGBoost	73.75	73.99	74.05	73.75		

Fig. 1. Random Forest achieved **74.40 accuracy, 74.78 precision, 74.77 re- call, and 74.40 F1-score**, outperforming **XGBoost (73.75)** and **SVM (73.40)** in prediction performance.

Healthcare Monitoring Dataset Loaded

Total Records: 10000 | Classes: High Risk, Low Risk | Train Samples: 8000 | Test Samples: 2000

Heart Rate	Body Temperature	Oxygen Saturation	Systolic Blood Pressure	Diastolic Blood Pressure	Age	Gender	Weight (kg)	Risk Categ
60	36.861707108012936	95.70204560529264	124	86	37	Female	91.54161781042704	High
63	36.51163284237428	96.68941321884792	126	84	77	Male	50.70492136378624	High
63	37.05204858016934	98.50826478317362	131	78	68	Female	90.3167596936639	Low F
99	36.65474750485421	95.01180149205474	118	72	41	Female	96.00618785155216	High
69	36.97509754422735	98.6237917407539	138	76	25	Female	56.02000582141864	High
79	36.88497906258021	95.9871292033958	130	70	22	Male	79.86993283621617	Low F
81	37.273639584377314	99.45671576538214	118	84	43	Male	57.84656504041972	High
96	36.85263343367673	97.1241246758814	135	77	72	Female	71.758971665616	High
83	36.04419142105122	98.58449733479578	111	84	50	Male	79.29533165339934	Low F
66	36.95717841280944	97.91626727887888	131	77	61	Male	53.923400264374514	High
84	36.27982119835746	98.19939668167716	119	84	35	Female	71.8911298271864	Low F
84	36.53178753600392	97.9974013231997	137	83	78	Female	99.3141136407496	Low F
72	37.23706954181399	96.58725178890396	112	76	31	Female	50.86972626145258	High
61	36.50556429762609	96.53272472086178	112	80	45	Female	82.22939150076127	High
98	37.2615339220957	98.6748399215955	127	87	89	Female	97.43162012894342	High
99	36.92458635485272	99.99858724037917	121	74	79	Male	60.62135938618223	High

Fig. 2. Dataset

III. PROPOSED METHODOLOGY

The methodology of this project focuses on the design and implementation of a powerful Live Health Monitoring System which aims at the correct classification of people as Low Risk and High Risk groups based on physiological information. It is a system that utilizes structured health records and cutting- edge machine learning capabilities to deliver timely warnings and pre-emptive health hazard measures. The procedure is outlined in details below with special attention paid to main steps, design decisions and rationales.

This flowchart shows all the crucial phases of the Live Health Monitoring System, including the collection of the data and real-time decision support, beginning and ending. The first in the process is the collection of health data, and the method will need the application of the IoT-linked or manually controlled devices to collect spreads of patient vital. These will be blood oxygen saturation, heart rate, temperature, and pressure. This infor- mation is then transmitted to the front-end interface. written in JavaScript, HTML, and Bootstrap, the system provides patients and medical workers with an opportunity to engage with the system by using a convenient dashboard. To train the machine learning, the data collected is sent to the backend to be preprocessed, that is, cleaned, missing values, from the collected data, normalized, and the features in the data were encoded. Random Forest model employs preprocessed information to determine the level of risk and prediction of patient fall. either a high-risk or low-risk one.

A. Overview And Motivation

Overview and Motivation: In the past years health has greatly improved. weighing tools that are supposed to identify the challenging health problems. The project objective is to collect physiological data, i.e. vital signs such as blood pressure, body temperature, heart rate, and oxygen saturation temperature, and correlate it with demographic information, e.g. age, gender and weight, to dynamically evaluate the level of health risk of every person.

The system is premised on obtaining quality. health in- formation. The collection is continuous and categorical and can be considered to be representative of varied physiological criteria. This data is most importantly correct and the integrity of this data impacts the performance of the model, therefore it must be. Physiological indicators: body temperature (degree Celsius), heart rate (beats per minute), oxygen saturation, systolic, diastolic blood pressure, and the percentage of SpO 2 (millimeters Hg). Demographic data consists of weight (kg) (male/female), age (years), and gender. Risk marks: two bit categorization labels representing a low risk and high risk hazard. There are flaws in real-world medical data in missing values, background noise, and inconsistency. Through the solution of these problems, the preprocessing method is meant to create clean and consistent model inputs. Normalization is being carried out. The Z-score is used to make numerical characteristics normalized. Uniform size and alignment is encouraged by model normalization. Categorized Variables: The gender will be coded by means of label encoding (Male=1, Female=0) so that data in text can be translated into integers. Correlation to Select Features Analysis is used to find and remove unnecessary or superfluous elements that might cause bias or noise. Maintaining Class Balance: Class imbalance is solved using techniques like Synthetic Minority Over- Sampling Technique (SMOTE). Training is used to eliminate majority-biased classes through goal.

COMPONENTS	SPECIFICATIONS
PROCESSOR	INTEL I5 / HIGHER(ARM)
RAM	MIN 4GB
STORAGE	AT LEAST 50GB
INPUT DEVICES	KEYBOARD,MOUSE
OUTPUT DEVICES	REQUIRED FOR LIVE DATA STREAMING
SENSOR	PULSE SENSOR,TEMPERATURE SENSOR,BP MONITOR,ETC

TABLE I HARDWARE REQUIREMENTS

SOFTWARE/TOOL	PURPOSE
HTML/CSS/JAVASCRIPT	FRONTEND DEVELOPMENT
PYTHON 3,X	BACKEND LOGIC AND ML INTEGRATION
FLASK/ DJANGO	PYTHON WEB FRAMEWORK FOR BACKEND API'S
CHART.JS/D3.JS	VISUALIZATION OF LIVE HEALTH DATA ON DASHBOARD
SCIKIT-LEARN	FOR IMPLEMENTING THE RANDOM FOREST MODEL
DATA(MY SQL/SQLITE)	STORAGE OF USER CREDENTIALS AND HEALTH DATA
VISUAL STUDIO CODE/ PYCHARM	CODE EDITOR/ IDE FOR DEVELOPMENT
XAMPP/WAMP	FOR RUNNING LOCAL WEB SERVER IF NEEDED
GIT	VERSION CONTROL SYSTEM

TABLE II Software Requirements

B. Testing Strategy and Tools Used

The system's dependability was guaranteed by using an organized testing methodology. Proper functionality of each of the modules was checked by unit testing. Postman was utilized in order to analyze API endpoints to check the functionality of the request and response processing. Also, load testing was provided by making forged patient data, making it possible to test the system in the areas that were similar to the real time usage. The Live Health Monitoring System is created with the application of a wide range of frontend and backend technologies. The user interface was built on HTML, Bootstrap, and JavaScript and has a user-friendly and responsive layout compatible with numerous devices. JavaScript also enabled the program to incorporate elements of interaction, whereas Bootstrap served to establish a common visual language.

Prediction \Actual	High Risk(1)	Low Risk(0)
High Risk (1)	743(TP)	135(FP)
Low Risk(0)	316(FN)	756(TN)

TABLE III PREDICTION TABLE

The server side made use of Python and Flask to allow the Python language to serve as the API connection as well as the work routing and perform the background duties. One of the machine learning components was an array of libraries including NumPy, Pandas, and Scikit-learn. Effective data handling and numerical processing were achieved with pandas and NumPy whereas data modeling training and testing were performed with Scikit-learn. The data and model performance were plotted in Matplotlib and Seaborn which created helpful graphical plots such as performance curves and distribution plots.With the help of these visualization tools, various graphs were generated to be more aware of the data and the per- formance of the model. These are performance curves (such as accuracy or loss graphs) and distribution plots which depict the distribution of data. The visual representations simplify the process of analyzing the results and making the conclusions.

IV. SYSTEM DESIGN

A. System Architecture of a Live Heath Monitoring System

Frontend Interface: The system begins with an HTML, CSS, and JavaScript web-based interface to provide the user with an easy and interactive interface. The vital health in- dicators that the user can input using this interface include heart rate, body temperature, respiration rate, diastolic and systolic blood pressure, as well as oxygen saturation (SpO 2). Anyone who does not have technical experience can just fill in his/her information and get instant feedback about the state of his/her health due to the direct design of the layout. Backend Processing: The backend (bridging of the machine learning model and user interface) is built upon a web framework developed in Python. The information transmission to the server occurs after the user provides information about his or her health information and is processed and analyzed and then predictions made. Data Preprocessing Layer: The input data is put through a number of preprocessing procedures to guarantee accuracy and consistency before the model is evaluated. Such procedures include processing ambiguous or unfinished values, repositioning or normalizing the numerical inputs, and trans- forming the information so that the model being utilized may comprehend. This preprocessing step is critical to maintaining accurate forecasts and ensuring a smooth flow of user inputs on the machine learning pipeline.

B. Libraries Used

Libraries Used: Python libraries like Pandas, NumPy, Scikit- learn, and SciPy are used in the implementation. These are tools that are used to administer the activities of model building, numerical, and data analysis. This layer is a prelim- inary stage where the raw input data undergoes a systematic, stepwise cleaning, organization and processing into a form that the machine learning model can utilize. It is also necessary to ensure consistent performance, improve the reliability of predictions, and to maintain the overall robustness of the model, so that proper preprocessing is necessary.

V. RESULTS

Here, the findings of the Live Health Monitoring System that applies real-time vital inputs and a machine learning model made by means of the Random Forest algorithm to classify the patient health conditions as low- and high-risk are described. The model was trained and evaluated using a healthcare dataset, which consists of such variables as heart rate, body temperature, oxygen saturation (SpO2), respiration rate, systolic and diastolic blood pressure.

Evaluation of Model Performance: The Random Forest classifier was developed based on important physiological parameters of heart rate, body temperature, breathing rate, systolic and diastolic blood pressure, and SpO 2 levels. In order to make the model more predictable and perform better, the data went through preprocessing prior to training and was cleaned, missing values corrected, and normalized. Some of the algorithms tested in course of the trial, but the better ones included Random Forest as well as Support Vector Machine (SVM) whose accuracy levels stood above 95 percent in diagnosing any aberrant health situation. The criteria of evaluation, such as precision, recall, F1-score and matrix analysis of confusion have proven that the model is highly reliable and able to differentiate between normal and critical health conditions.

The system was challenged with a dynamic user interface which facilitates continuous monitoring of the health param- eters. It also generates notifications in case of an anomaly reading in order to ensure timely action. The fact that the system can accept real-time data input and process it efficiently and very fast was confirmed by the fact that the system has been tested in a deployment environment, which means that it is suitable to use the system in real-time applications. Analysis of Feature Importance: In the study of feature importance as presented by the random forest model, oxygen saturation (SpO 2) was the most impactful during prediction outcomes. Heart rate and systolic blood pressure followed, as they are considered significant measures of health risk. Other consid- erations such as body temperature, rate of respiration and diastolic blood pressure made important contributions, though at a lower extent. These findings indicate the reliability of the model and agree with the established medical knowledge.

Validation and Performance Metrics: The confusion matrix data established very low misclassification rates with little false positive and false negative. The Receiver Operating Characteristic (ROC) curve had an excellent performance with a value of Area Under Curve (AUC) of about 0.97, which indicates the high ability of the model to differentiate different medical issues.

In general, the system was consistent at all levels, such as real-time deployment, model training, and data processing. The solution can be used as a viable solution to early risk detection and remote health monitoring, as it has the ability to make accurate predictions with very little latency.

VI. CONCLUSION

This analysis demonstrates the steps to develop and implement successfully a Live Health Monitoring System that is capable of measuring health risk levels based on the vital parameters that are provided by the user. The system uses a machine learning model based on the random forest to assess and categorize individuals into low-risk or high-risk groups based on vital signs such as heart rate, body temperature, oxy- gen saturation (SpO 2), respiration rate, and blood pressure. The accuracy of nearly 92 achieved by the model shows that the model has the capacity to make correct prediction without compromising economical use of computers. This is another indication of how ensemble learning techniques can perform well in structured medical data where stability and accuracy are paramount. The proposed system offers a web-based platform, which allows constant and remote observation, unlike the traditional healthcare systems that use direct-person communication and manual observation. Django back-end and HTML, CSS and JavaScript front-end will give ease of access and usability to a wide range of users. Due to this fact, the method is particularly useful in areas where medical facilities are limited in access. On the whole, the investigation enhances the intelligent healthcare systems by integrating predictive analytics with real-time data processors. By making it possible to identify possible health hazards early on, it encourages a move to- wards preventative care. A more advanced algorithm, such as XGBoost or deep learning models, real-time data collection via wearable or IoT sensors, and the ability to store long-term health records in the cloud, as well as multi-class classification of specific medical conditions, are only a few examples of how the system could be enhanced.

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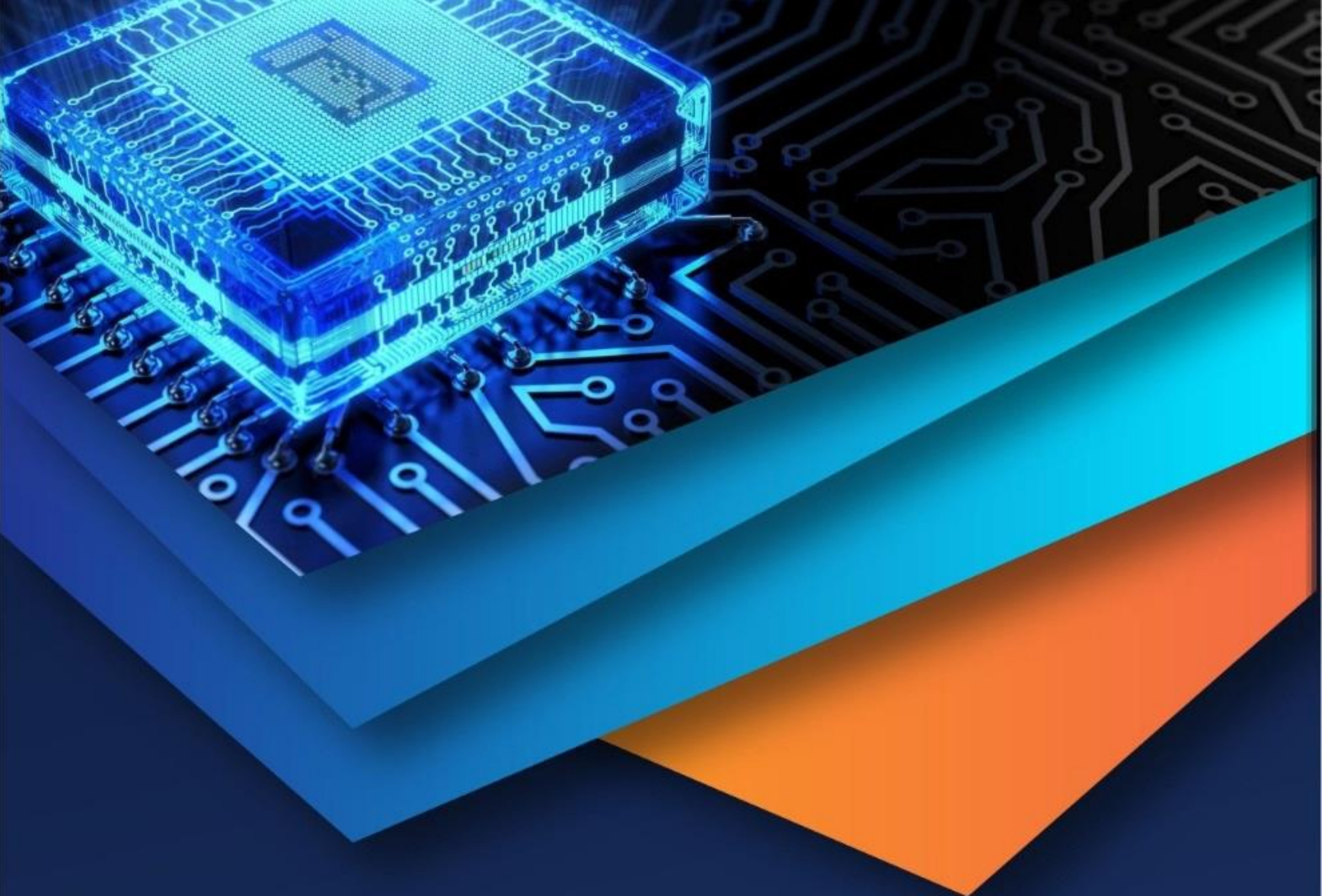

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