iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.79968

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Human Stress Detection Based on Sleeping Habits Using Random Forest

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Abstract: ***Stress, which is most common part of contemporary life, can have a serious negative effect on a person's physical and mental health. Determining and tracking stress levels is therefore essential to improving general health and quality of life. This offers a cutting-edge and successful method for determining a person's degree of stress by looking at how they sleep. Utilizing the robust features of the Python programming language, the research makes use of the Random Forest Classifier algorithm, which is renowned for its adaptability and precision in classification assignments .The primary objective is to develop a reliable stress detection system more that can provide insightful data about people's stress levels, enabling timely interventions and promoting improved mental health. Numerous significant variables related to stress levels and sleep patterns are included in the data set that was carefully chosen for the study. The user's snoring range, respiration rate, body temperature, limb movement rate, blood oxygen levels, eye movement, heart rate, number of hours slept, and stress levels—which are divided into five classes—are among these parameters. The classes are 0 (low/normal), 1 (medium low), 2 (medium), 3 (medium high), and 4 (high). By including these several criteria, a thorough examination of sleep patterns and their relationship to stress levels is ensured. The model was able to learn complex patterns from the data set and forecast stress accurately based on the user's sleeping patterns, as seen by the high accuracy that was attain. Research and treatments in medicine as well as personal health monitoring are just a few of the many possible uses for this stress detection system. People can take proactive steps to reduce stress, enhance sleep quality, and promote general well being by using the system to analyze their sleep patterns and receive insights into their stress levels.***

Index Terms: Random Forest Classifier algorithm ,Confusion Matrix.

I. INTRODUCTION

An essential aspect of human existence, stress is a complex reaction to a range of internal and external pressures that disturb a person's emotional, physical, or mental balance. Humans face several stressors as they make their way through the complexity of daily life. These stressors might include various financial constraints, personal relationships, professional pressures, health-related issues, and more. Although stress is a necessary survival mechanism that primes the body for fight-or-flight reactions in life-threatening circumstances, chronic or extreme stress can be harmful to one's general health. The stress response, sometimes known as the "fight or-flight" response, is the body's physiological and hormonal response to stress. The adrenal glands release cortisol and adrenaline while under stress, which raises blood pressure and causes a rise in heart rate and behavioral responses to stress. Machine learning algorithms, such as Random Forest Classifier and Naïve Bayes, offer powerful tools for analyzing these data and predicting stress levels based on various parameters. Technological and data analytic advancements have created new avenues for stress identification and management. Large-scale data collection on people's physiological and behavioral reactions to stress is now feasible because to wearable technology and health monitoring systems. Strong tools for evaluating these data and forecasting stress levels based on several criteria are provided by machine learning algorithms like Naive Bayes and Random Forest Classifier. Finding out how human stress varies according to sleeping patterns is the main objective of this study. The particular goals also include how human stress and sleeping habits are related, what primary sleeping behaviors influence a person's stress level, what methods are available for detecting human stress, and lastly, how to detect human stress based on sleeping habits. In order to better understand the relationship between stress levels and sleep patterns, the study . This aims to develop an accurate and efficient stress detection system through the use of sleep-related data and machine learning techniques. This can furnish individuals with significant information regarding their stress levels, so enabling prompt interventions and proactive stress management.

II. LITERATURE SURVEY

Human Stress Detection Based on Sleeping Habits Using Machine Learning Algorithms aims to analyze and interpret an individual's sleeping patterns to assess stress levels. By collecting data such as sleep duration, interruptions, and quality, machine learning models can identify stress-related anomalies. These systems leverage wearable devices or smartphone applications for data collection. Advanced algorithms process this information to predict stress levels and provide actionable insights. The approach facilitates early detection, allowing users to take preventive measures to improve mental well-being. The system is scalable and adaptable to individual habits, enhancing its accuracy over time. It can integrate with other health metrics like heart rate for comprehensive analysis. This innovation promotes personalized healthcare and reduces dependency on manual stress assessments. Additionally, the solution emphasizes privacy, ensuring secure handling of sensitive user data. The technology holds potential for both personal and clinical applications, bridging the gap between technology and mental health management[1].

A Stress-Detection System Based on Physiological Signals and Fuzzy Logic utilizes biometric data like heart rate, skin conductivity, and blood pressure to identify stress levels. Fuzzy logic algorithms process these signals to handle uncertainty and provide precise stress level assessments. This system offers real-time monitoring and actionable insights, making it suitable for personal and clinical use. It adapts to individual variations, ensuring personalized and accurate results. The technology emphasizes non- invasive methods and promotes mental health awareness with advanced computational techniques[2]. support vector machines for accurate predictions. Designed for scalability, it supports diverse applications, from workplace stress management to clinical therapy. The system also enables real- time monitoring and feedback, fostering proactive stress interventions. Its adaptability ensures accurate detection across different demographics and environments. By offering personalized insights, the framework promotes mental health and well-being [3].

III. SYSTEM OVERVIEW

Bayes for depression, giving them the highest f1 score. An ML framework based on the electroencephalogram (EEG) signal analysis of stressed individuals was presented in the study. In the lab, stress was created using a well-liked evaluation technique based on the Montreal Imagining Stress Task. The objective feedback and work performance both corroborated the introduction of stress. The EEG feature extraction and selection (using the t-test,ROC curve, and Bhattacharya distance), logistic regression, regression analysis, SVM classification, and Naive Bayes models were all included in the Machine Learning Framework for the Detection proposed machine learning model. The results show of Mental Stress at Multiple Levels employs advanced algorithms to analyze physiological and behavioral data for stress identification. It integrates data from sources such as heart rate, skin temperature, and activity levels to assess stress intensity. The framework categorizes stress into multiple levels, providing a granular understanding of the user's mental state. It leverages techniques like deep learning and and determining which sleep metrics are most important for identifying stress. Using bio physiological indicators such as respiration, body temperature, GSR data, and upper body position sensors and accelerometers on the arms and body, they develop and assess various classification models. Using the classification models, they were able to develop person-independent models that differentiated between three stress levels: low, moderate, and high. Out of all the algorithms, SVM produced the best classification accuracy of 73%.

The output percentage shown in fig[1].

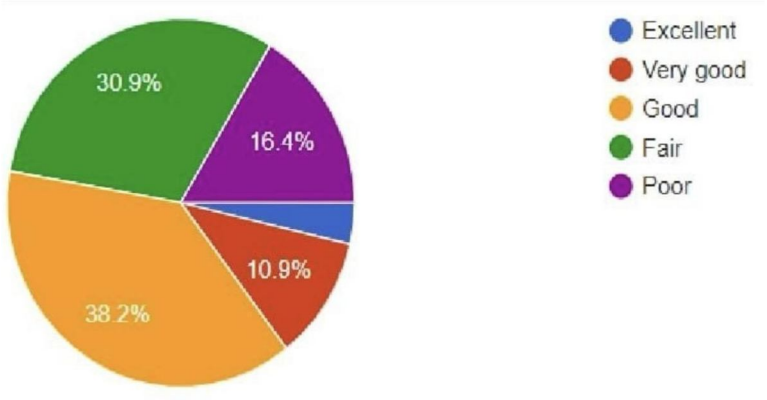


Figure 1: Percentage of output

IV. METHODOLOGY

The primary goal of the study is to forecast human stress by analyzing sleep-related behaviors. There are five suggested approaches. They are Data Collection, Dataset, Data Preparation, Splitting the Dataset and Model Selection as shown in Fig. [2].

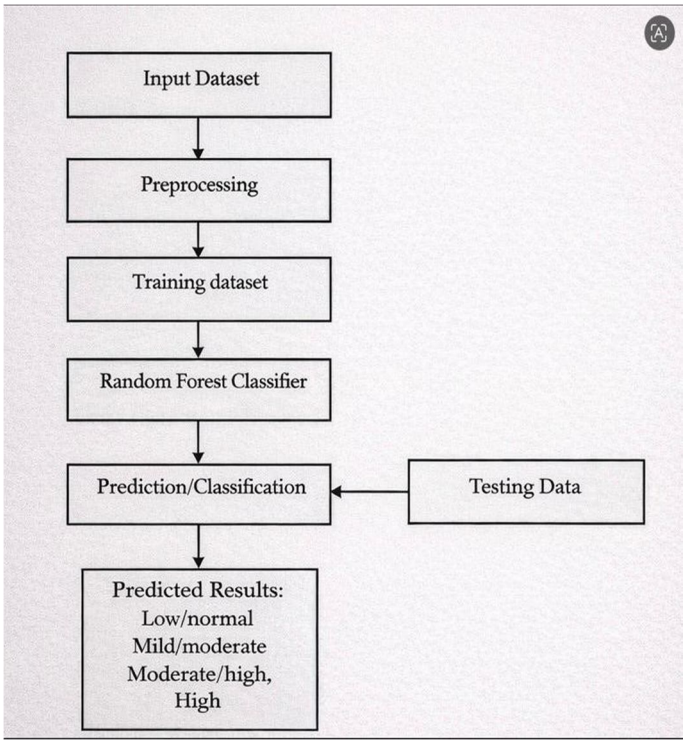


Figure 2: Architecture of the study

A. Data Collection

Data Collection: Human Stress Detection Based on Sleeping Habits's first module To obtain the input dataset, we created the system using machine learning algorithms. The process of gathering data is the initial step in the actual building of a machine learning model. This is a crucial stage that will have a cascading effect on the model's quality; the more and better data we collect, the more capable our model will be. There are various methods for gathering the data, including manual interventions and online scraping. Our dataset may be found in the model folder of the project. The dataset is sourced from Kaggle, a widely used standard dataset repository that is used by academics worldwide. There are numerical data in the dataset.

B. Dataset

The dataset consists of 630 individual data. There are 9 columns in the dataset , which are described below.
SR - Snoring Range. RR
Respiration Rate. T - Body Temperature.
LM - Limb Movement Rate. Bo

Blood Oxygen.
REM - Eye Movement.
SR1 - Number of Hours Sleep. HR - Heart Rate
SL - 0- Low/Normal, 1 – Medium Low, 2- Medium, 3-Medium High, 4 –High

C. Data Preparation

Sort through data and get it ready for training. Clean up anything that could need it (get rid of duplicates, fix mistakes, handle missing values, normalize, convert data types, etc.). Data can be made random to eliminate the impact of the specific order in which it was gathered and/or prepared. Use data visualization to carry out additional exploratory analysis or to identify pertinent correlations between variables or class imbalances (bias alert!). Divided into sets for training and assessment.

Number of Steps involved to input dataset , training ,testing and predicted results Shown in Fig [3].

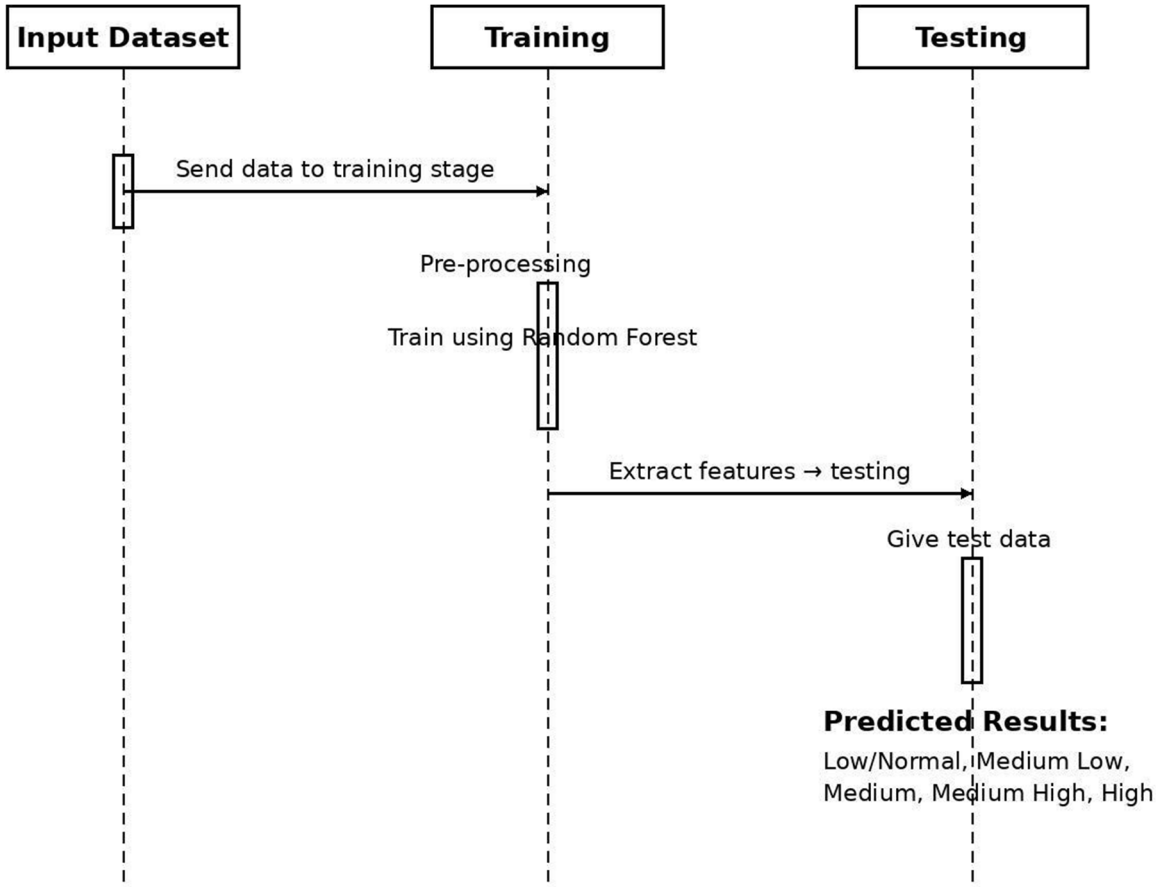


Figure 3 : Dataset , Training ,Testing and Predicted results

D. Splitting the Dataset

In this module, the image dataset will be divided into training and testing sets. Split the dataset into Train and Test. 80% train data and 20% test data. This will be done to train the model on a subset of the data, validate the model's performance, and test the model on unseen data to evaluate its accuracy. Split the dataset into train and test. 80% train data and 20% test data.

E. Model Selection

We used Random Forest Classifier machine learning algorithm, we got a accuracy of 97.6% on test set so we implemented this algorithm.

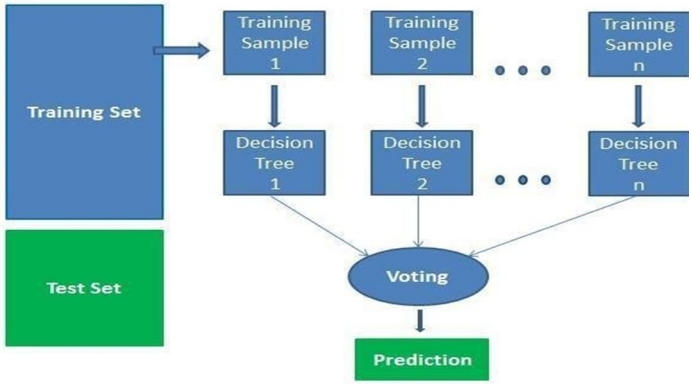


Figure 4: Model selection

F. The Random Forests Algorithm

A group of decision-making trees cooperating to generate predictions is how the random forest classifier functions. To make its choice, every tree in the forest considers a random subset of information and a random collection of characteristics. Next, every tree casts a vote to choose the winning forecast. It leverages several trees, which makes it effective in processing large and complex data sets. However, it occasionally has a slowdown and performs poorly with noisy data. All things considered, it's a well-liked and effective machine learning tool.The Random Forest Classifier facilitates the identification of the most relevant characteristics that contribute to stress level forecasts by offering a measure of feature importance. By ensuring that only major and pertinent features are taken into account, this feature selection procedure improves the effectiveness of the model and lessens the influence of unimportant traits. Random Forest is renowned for its ability to withstand outliers, reducing the potential for disruption in its ability to anticipate stress levels. When working with real- world sleep data, which occasionally contains outliers owing to a variety of reasons, this feature is really helpful.

V. EXPERMENTAL RESULTS

In machine learning, prediction is the process of employing a trained model to infer probabilities or estimates regarding novel, unseen data points by applying patterns discovered during training from a labeled dataset. Initially, input data with features comparable to those in the training data are given to the model. Before the input data is fed into the model, it is pre-processed to extract pertinent features. Subsequently, the model employs the patterns it has learnt to provide predictions. These predictions might be class labels for classification tasks or continuous values for regression tasks. The model's performance is assessed using a variety of indicators once it has made predictions. Once it has been verified, the model can be used for practical purpose. A technique for identifying and managing physiological stress related to eating habits on the Internet of Medical Things (IoMT) has been presented in the study. Additionally to these pieces, they provide SaYoPillow, a device that tracks and regulates a person's stress levels while they slumber. The primary goal of SaYoPillow is to accomplish "Smart- Sleeping," which is a thorough sleep that meets the ideal body requirements for sleep. SayoPillow proposed a real-time physiological signal detecting to adjust the quality of sleep by considering parameters like heart rate range, snoring range, respiratory rate range, number of hours of sleep,oxygen in blood range ,movement rate,duration of Rapid Eye Movement(REM), change in body temperature, and limb movement rate. Any snoring rate more than 50dB increases the risk of tension and other health problems.

In breathing 15 to 17 breaths per minute (bpm) are considered to be a good breathing rate. When a person is sleeping, their heart beats five to ten times slower than usual. Due to the detrimental effects of sleep deprivation on one's health, adults should aim for at least 7 hours of sleep each night. Next, it is advised that 20–25 percent of the amount of sleep be spent in rapid eye movement (REM), which equates to about 90 minutes for 7-8 hours of sleep. When oxygen saturation drops below 90%, it is deemed abnormal and stressful. 348 men and women, working and unemployed, performing a variety of tasks from housework to professional responsibilities, between the ages of 20 and 60, participated in the study ML framework for the monitoring mental stress at multiple levels . According to their findings, Random Forest scored 90% for stress and Naive.

VI. LEVELS OF STRESS

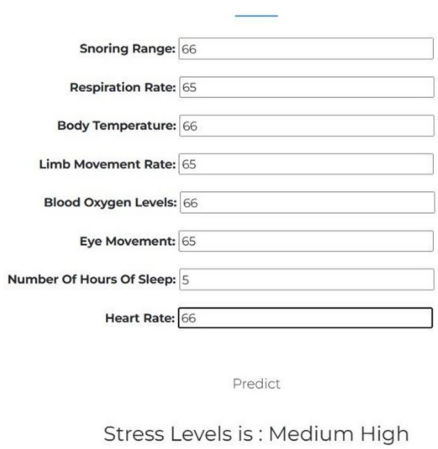
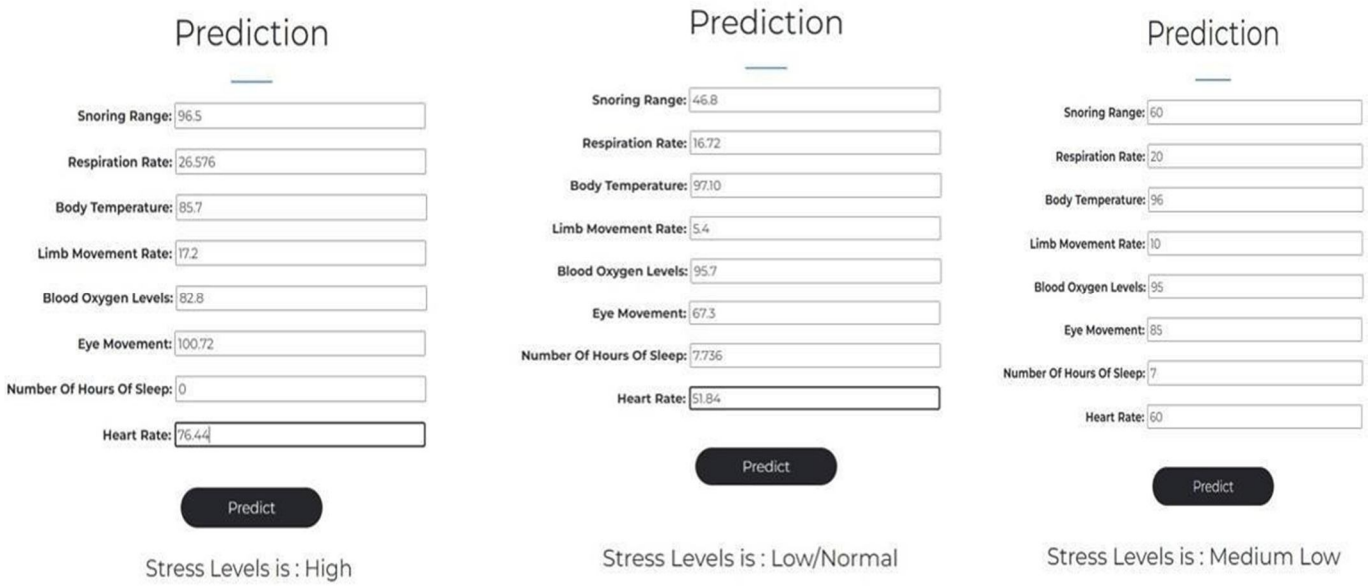


Figure 5: Stress levels of proposed work



VII. PROPOSED SYSTEM

Stress, an increasingly prevalent aspect of modern life, can significantly impact an individual's physical and mental well-being. Hence, understanding and monitoring stress levels play a crucial role in promoting overall health and quality of life. The project "Human Stress Detection Based on Sleeping Habits Using Machine Learning with Random Forest Classifier" presents a novel and effective approach to detect human stress levels by analyzing their sleeping habits Leveraging the powerful capabilities of Python programming language, the study employs the Random Forest Classifier algorithm, known for its versatility and accuracy in classification tasks. The data set used in this study is carefully curated and comprises various essential parameters related to both sleep patterns and stress levels. These parameters include the user's snoring range, respiration rate, body temperature, limb movement rate, blood oxygen levels, eye movement, the number of hours of sleep, heart rate, and stress levels categorized into five classes: 0 (low/normal), 1 (medium low), 2 (medium), 3 (medium high), and 4 (high). The inclusion of these diverse parameters ensures a comprehensive analysis of sleep patterns and their correlation with stress levels.The results of the experiments reveal a Training score of 100% and an impressive Test score of 97%, demonstrating the effectiveness and robustness of the proposed methodology. The achieved high accuracy showcases the model's capability to learn intricate patterns from the data set and make accurate stress predictions based on the user's sleeping habits.

System is scalable and adaptable to individual .habits, enhancing its accuracy over time. It can integrate with other health metrics like heart rate for comprehensive analysis. This innovation promotes personalized healthcare and reduces dependency on manual stress assessments. Additionally, the solution emphasizes privacy, ensuring secure handling of sensitive user data. The technology holds potential for both personal and individual.

VIII. CONCLUSION AND FUTURE WORK

In the area of stress management and sleep analysis, the "Human Stress Detection Based on Sleeping Habits Using Machine Learning with Random Forest Classifier" study is significant. The research attempts to accurately estimate human stress levels based on sleeping habits by implementing the RandomForest Classifier algorithm and carefully taking into account various sleep-related data.

Better accuracy, resilience to outliers, and the capacity to manage non-linear correlations between stress levels and sleep metrics are just a few of the benefits that the suggested approach offers over the current one. Utilizing feature importance analysis and continual learning, the system guarantees flexibility to evolving sleep patterns over time and offers insightful predictions of stress levels. The initiative streamlines the data through a number of clearly defined modules.At the heart of the system is the Random Forest Classifier module, which uses a group of decision trees to classify stress levels in an accurate and well-informed manered.

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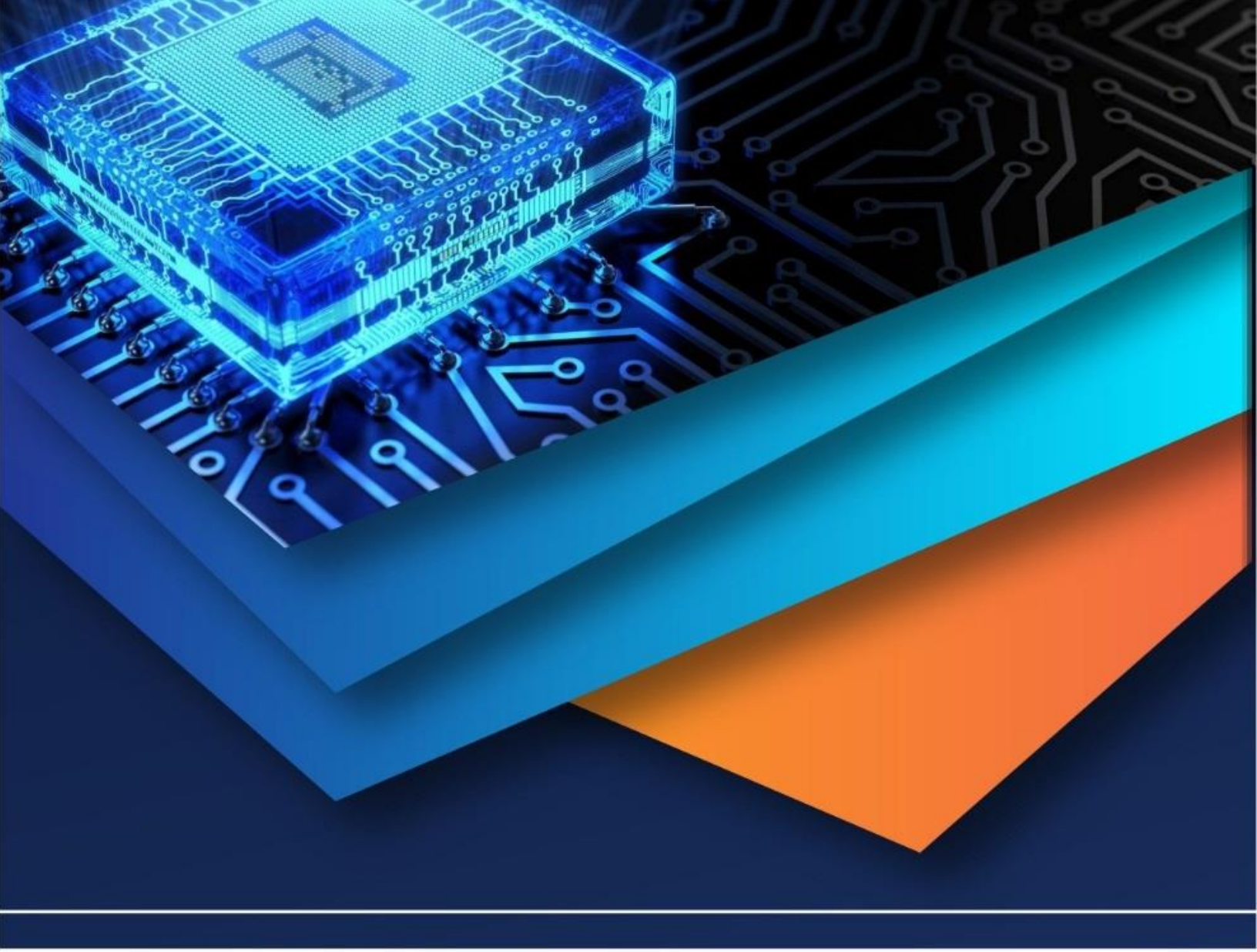

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