iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL
FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: XI Month of publication: November 2023

DOI: https://doi.org/10.22214/ijraset.2023.56895

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue XI Nov 2023- Available at www.ijraset.com

A Comprehensive Review of ECG-Based Sleep Apnea Detection

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Abstract: Sleep apnea (SA) is a typical rest problem which could disable the mortal physiological frame. Hence, early determination ofSA is of extraordinary interest. The conventional fashion for diagnosing SA is a short- termpolysomnography (PSG) assessment. At the point when PSG has confined availability, programmed SA webbing with a lower number of signs ought tobe allowed of. The main part of this study is to produce and assess a SA position model in view ofelectrocardiogram (ECG) and blood oxygen absorption (SpO2). We embraced a multimodalway to deal with immingle ECG and SpO2 signalsat the include position. also, highlight determination was led exercising the recursive element disposal with cross-approval (RFECV) computation and random forest (RF) classifier used to insulate between apnea and typical occasions. Tests were led on the Apnea- ECG information base. The presented computation got aperfection of 97.5, a responsiveness of 95.9, an explicitness of 98.4 and an AUC of in per-section grouping, and beat once workshop. The issues showed that ECG also, SpO2 are complementary infeting SA, and that the mix of ECG and SpO2 improves the capacity to dissect SA. Accordingly, the proposed fashion can conceivably be an optionto traditional discovery strategies.
Keywords: CNN (Convolution Neural Networks), Deep learning, SVM (Support Vector Machine), KNN (K-Nearest Neighbor), ABCD (Asymmetry, Border, Color, Diameter), Dermoscopic, Pre-processing, Feature Extraction, Segmentation, ApEn (Approximate Entropy).

I. INTRODUCTION

Sleep apnea (SA) is a common sleep complaint, alsogenerally known as obstructive sleep apnea (OSA).The clinical presentation of SA is a conclusion of nasal airflow or a drop in airflow intensity by further than 30 compared to the base position, but the corresponding breathing movements are maintained. At the same time, oxygen desaturation decreases by further than 4 for further than 10 s. The prevalence of OSA in adults ranges from 9% to 38%, increasing with age Low-quality sleep accompanied by apnea generally leads directly to poor attention, memoryloss, slow response, and depression. In addition, OSA is a implicit trouble to numerous physiologicalsystems of the mortal body, especially thecardiovascular system. It can induce hypertension,heart failure, coronary roadway complaint, diabetes,and other conditions, which seriously hang the healthof cases. If patients are diagnosed and treated at an early stage of OSA, the health risks can be mitigated. Thus, timely diagnosis of cases with OSA isessential. Clinically, polysomnography (PSG) is the reference standard for the diagnosis of SA.PSG is effective in covering sleep conditions by collectingcolorful physiological signals similar aselectrocardiogram (ECG), electroencephalogram(EEG), electromyogram (EMG), blood oxygen desaturation (SpO2), airflow signals, respiratorytrouble still, wearing too numerous detectors duringphysiological signal collection can beget discomfortto the case. In addition, the diagnosis of OSA requiressleep specialists to spend a lot of time manually assaying PSG data. Thus, automatic discovery of SA using smaller signals is necessary.

Experimenters have generally developed SA discovery algorithms using ECG signals. ECG is a non-invasive fashion for recording the electrical exertion of heart and the physiological exertion of heart is regulated under the autonomic nervous system (ANS). Clinically, heart rate variability (HRV) is an important index of the outgrowth of ANS regulation. Thus, it's doable to screen for apnea by covering ECG during sleep. Yet, ECG signals are fluently told by cardiovascular complaint status. This makes the diagnosis of SA more grueling. piecemeal from ECG signals, SpO2signals are also extensively used to descry SA as the lack of respiratory effort due to SA events can lead to a drop in SpO2. repetitious oxygen desaturation islargely specific for apnea. still, the perceptivity of oximetry is generally low, as not all apnea events lead to perceptible desaturations. Therefore, SpO2 alone or ECG alone can be used as an implicit individual means of SA, but not as a dependable means. With technological advances in detectors and low-power bedded systems, the collection of physiological signals has come easier and further provident. Thus, we consider using multiple signalsto develop a further dependable discovery algorithm of SA, rather than being limited to a single signal.

This study explores the effectivenessand trust ability of a multimodal approach to the automated discovery of SA events using a combined channel of ECG and SpO2.

To this end, we uprooted features from ECG signal and SpO2 signal independently, and also fused the features ofthe two different modalities. point selection was performed using the recursive point elimination with cross-validation (RFECV) algorithm. The named features were fed to the RF classifier to identify sleep apnea events. Our study provides three main benefactions to exploration. First, we corroborate the complementarity of ECG and SpO2signals to automatically descry SA. When the two signals are combined, the individual capability is increased. Second, the RFECV algorithm is employed to elect the most important features. The proposed SA discovery fashion uses a lower number of features and is computationally affordable compared to utmost of the being styles. Third, we enrich the system in the field of theautomated discovery of SA by applying a multimodal approach to fuse ECG and SpO2signals at the point position. So far, utmost of theextant literature primarily used SpO2 alone or ECGalone, but didn't consider the combination of ECGand SpO2.

II. RELATED WORKS

Optimization of Sleep Apnea Detection using SpO2 and ANN - Repetitious respiratory disturbance during sleep is called Sleep Apnea Hypopnea Syndrome and causes colorful conditions. Different features and classifiers have been used by different experimenters to descry sleep apnea. This study is accepted to identify the better performing blood oxygen desaturation features subset using an Artificial Neural Network classifier for sleep Apnea discovery. A database of 8 subjects with one- nanosecond reflection is used to test the proposed system. The optimized system has seven features chosen from a total set of sixty- one features presenting a high delicacy rate using a inheritable algorithm. The Artificial Neural Network achieved a 97.7% accuracy rate using only seven features selected by the genetic algorithm. Another popular signal is blood oxygen desaturation (SpO2), measured by palpitation oximetry which has some added advantage over otherdetectors. It's further movable and can be used in hypopneas where the drop in oxygen desaturation caused by a reduction in the airflow maturity of the cases no clear ECG changes can be detected. Time sphere and time frequency sphere features of SpO2 are used with a different classifier to descry Apneas event duly by different experimenters. It's essential to find a dominant and optimum subset of features for bracket because learning with all available features could have a negative effect on performance, particularly when inapplicable or spare features are present. That's why a system optimization of thefeatures for Artificial Neural Network (ANN) is demanded. In this work, a successful optimization of sleep Apnea discovery is carried out. It's showed thatthe delicacy achieves by combining the ANN with GA is relatively good. The features named by the GA algorithm are substantially time-frequency signal (four among seven) only two time and one frequency point is named. From this selection procedure, it's accessible that Apnea events have utmost of the information in time- frequency space. Compared to former work it improves the delicacy. In future, this work can be tested on different databases and classifiers. A limitation of the styles used at that time that the structure of the named MLP is calculated using a rule of thumb and experimental hunt which can be replaced, for illustration, by a GA algorithm and the trial isn't subject independent.

An Efficient Method to Detect Sleep Hypopnea-Apnea Events Based on EEG Signals - Sleep disturbances can lead to inadequate sleep at night and internal fatigue during the day, which can have a significant negative impact on our lives. The twomain grueling problems in sleep analysis are sleep stage scoring and apnea- hypopnea discovery. Hypopnea refers to a 30 drop in oronasal airflow and a 4 drop in blood oxygen desaturation for further than 10 seconds, or 50 drop in nose and mouth airflow and 3 drop in blood oxygen desaturation for further than 10s. In this paper, the three types of apneas are allocated according to a reasonable proportion proposed by the medical experts of respiratory conditions from Tianjin casket Sanitarium, the OSA is 60, and the MSA and the CSA are 30 and 10, independently. Since the characteristics of hypopnea- apnea pattern are different from other conditions, the symptoms first appear during darkness sleep, and alsopromote the development of cardiopulmonary failure. thus, it's particularly important to descry the presenceof hypopnea- apnea pattern in time. The proposed system finds the approximate entropy of the detail measure as characteristics of EEG signals during the apnea- hypopnea events. also a machine learning bracket model is established and results are attained on the test set as the final evaluation indicator of the point. Our model achieves the stylish result with delicacy94.33, perceptivity 93.10, and particularity 95.07 and provides a discovery system that uses the EEG signals to automatically descry the hypopnea- apnea events that do during darkness sleep.

Sleep Apnea Detection Using a Feed- Forward Neural Network on ECG Signal - Sleep Apnea is a sleep complaint characterized by conclusion of breathing during sleep that can last seconds or twinkles. In addition, sleep apnea is considered an important factor for morbidity and mortality due to it's direct effect on the cardiovascular system. These goods are associated with physiological functions similar as systemic hypertension and increased sympathetic exertion that compromise the heart. There are three different types of apnea central (CSA), obstructive (OSA) and mixed. This bracket is grounded on the respiratory trouble. CSA, causes the loss of allrespiratory trouble during sleep and is also generally marked by diminishments in bloodoxygen desaturation, while OSA is characterized by intermittent pauses in breathing during sleep caused by the inhibition of the upper airway.

The combination of these symptoms takes to mixedapnea. The symptoms associated to sleep apnea arefatigue, day somnolence, low response and visual problems. Entire population anyhow of gender, age or race can be affected by sleep apnea This paper presents a suitable and effective perpetration for detecting nanosecond grounded analysis of sleep apnea by Electrocardiogram (ECG) signal processing. Using the PhysioNet apnea- ECG database, a median sludge was applied to the recordings in order to gain the Heart RateVariability (HRV) and the ECG- deduced respiration (EDR). The posterior uprooted features were used for training, testing and confirmation of a Artificial Neural Network (ANN). Training and testing sets were attainedby aimlessly divide the data until it reaches a good performance using ak-fold cross confirmation (k = 10).According to results, the ANN bracket has sufficient delicacy for sleep apnea discovery and diagnosis (82,120). This promising early-stage result may leads to reciprocal studies including indispensable featuresselection styles and/ or other bracket models.

III. OBJECTIVES

1) The paper thoroughly examines the various methods and techniques used in sleep apnea detection throughECG data, providing readers with a clear understanding of the existing landscape, the evolutionof techniques, and the various approaches explored in this context.
2) The paper focuses on the Random Forest algorithm, delving into its application, strengths, limitations, andinstances where it has proven effective in the contextof sleep apnea detection.
3) Different data sources for ECG data used in sleep apnea detection, such as in-lab polysomnography,home-based monitoring, and wearable devices, are explored, highlighting their differences and their implications on the detection process.
4) The paper investigates feature extraction methods, making it easier for readers to grasp the technical intricacies involved in translating raw ECG data into meaningful information for sleep apnea detection. Preprocessing steps for ECG data, including noise reduction, artifact removal, and data augmentation,are evaluated, helping readers understand the significance of these steps and their impact on the accuracy and reliability of detection models. Specific performance metrics, such as sensitivity, specificity, accuracy, and F1-score, are explained, allowing readers to gauge the efficacy of sleep apnea detection models and their suitability in the context of ECG-based detection.
5) The paper addresses challenges and limitations in using ECG data for sleep apnea detection, including considerations like data quality,class imbalance, and the generalizability of models in diverse scenarios.
6) A comparative analysis is provided, comparing the Random Forest algorithm with alternative machine learning and deep learningapproaches used in sleep apnea detection, helping readers understand the relative advantages and disadvantages of each approach.
7) The clinicalrelevance of ECG-based sleep apnea detection is explored, shedding light on how this technology canimpact patient diagnosis, treatment, and healthcare practices from a reader's perspective.
8) The paper highlights emerging trends and research gaps in thefield, proposing potential future directions, providing valuable insights for researchers and stakeholders looking to advance this area ofstudy. Real world applications of ECG-based sleep apnea detection, such as telemedicine, remote patient monitoring, and personalized treatment strategies, are discussed, illustrating the practical significance of this research to readers.
9) Ethical concerns surrounding data security, patient consent, and privacy in the context of ECG-based sleep apnea detection are addressed, ensuring a well-rounded exploration of the subject matter fromthe reader's viewpoint.

IV. METHODOLOGY

A. *Proposed Framework*

1) The proposed framework involves the extraction of the features from the two modalities – ECG signal and SpO2 signal. The features are then fused and the essential features are selected for classifying the results. The flow diagram framework is as shown in figure 1.

B. *Preprocessing*

1) For the noise in the ECG signal similar as baseline drift and power frequency interference, we use FIR bandpass filter with passband of 350 Hz to denoisethe original ECG signal. Also, the entire ECG signal is segmented into 1- min parts by pertaining to the reflections in the database.
2) Grounded on the per- nanosecond ECG member, we use the Hamilton algorithm to detect the R peaks, and correct the position of the R peaks to the maximum value, so asto insure the delicacy of the R peaks discovery.

3) The RR interval signal is attained by the interval between consecutive R peaks, and the RR interval outliers are removed with reference to the system of the RAMP(RAMP signal is a type of standard signal which starts at $t = 0$ and increases linearly with time signal is attained by the breadth of R surge.
4) In particular, one of the simplest approaches to gain an EDR (ECG- deduced respiration) signal is by working in the RAMP signal, so the RAMP signal is also called the EDR signal.
5) SpO2 and ECG recordings are collected contemporaneously. also, the entire SpO2 signal is resolved into 1- min parts, and parts that violated its physiological significance (SpO2 values lower than 50) are removed (25). also, the RR interval signal, RAMP signal and SpO2 signal are used for posteriorpoint birth.

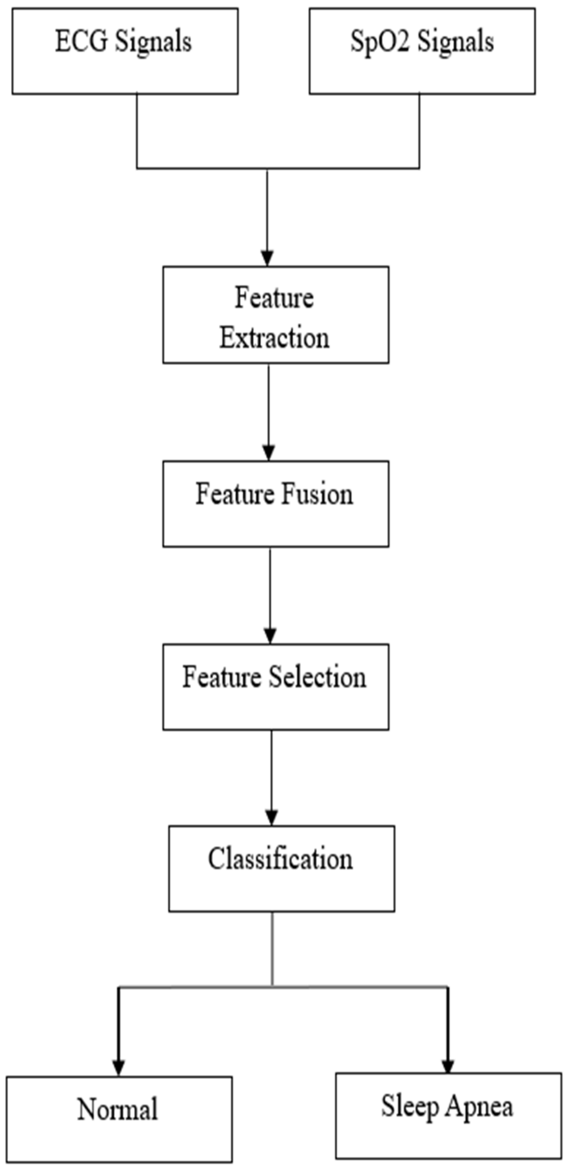

Figure 1: Flow diagram of Sleep Apnea Algorithm

C. Feature Extraction and Fusion
1) In this study, direct (time sphere and frequency sphere) analysis and nonlinear analysis styles were used to prize features.
2) We attained three sets of features from ECG and SpO2 signals, which were RRintervals features, R- surge confines features, and SpO2 features. The details of these features and emulsion strategy are described below.

D. SpO2 Features

1) Six features were calculated from the SpO2 signal. Grounded on statistical styles, Smin, Smean, and Svar are calculated from SpO2 parts.
2) Three generally used nonlinear features (ApEn, CTM, and LZC) are also added to the SpO2 point set.
3) The optimal parameters for calculating ApEn are a for bearance of 0.25 and an embedding dimension of 2, while LZC is a non-parametric dimension.
4) In addition,CTM calculates the rate of the number of points fallinginto the center in the origin region with compass R to the total number of points through the alternate- order difference graph. After point birth, in order to exclude the distribution differences between colorful types of features and speed up the confluence of the model, we regularize the features with the following equation

$$x* = x - x2/\sigma$$

where x is the unnormalized point, x represents the mean of the point, σ is the standard deviation of the point, and x ∗ is the regularized point.

E. Feature Fusion

1) In the field of machine literacy, multimodal emulsion is a fashion that integrates information from multiple modalities, including beforehand, latterly, and cold- blooded emulsion. Among them, early emulsion, also known as point- grounded multimodal emulsion, refersto the connection of features from different modalitiesbefore model training.
2) In this study, the ECG and SpO2 signals collected bydifferent detectors can be considered as two modalities.
3) In order to combine the information from different modalities, we fused the below three-point sets using an early emulsion strategy with the following way let In be the point vector of RR intervals, let Rn be the point vector of RAMP, and let Sn be the point vector of SpO2; also, the consecution of these threerepresentations In, Rn, and Sn produced a point vector of which the dimension is 24.

F. Random Forest

1) RF is an ensemble literacy model conforming of a set of decision tree classifiers fk(x, θk) k = 1, 2, · · ·, n(31), and the specific perpetration process is to use a randomized with put back approach(Bootstrap system) to prize the training set θk from the original sample set θ; also to use the tried training set θk to train the decision tree fk(x, θk).
2) When a new sample x is input to the arbitrary timber, all decision trees f(x) classify the new sample independently, and eventually determine by advancing the bracket results

$$Y = F(x) = \operatorname{argmax} \sum_{k=1}^{n} I(fk(x) = y),$$

where Y is the final result of the bracket, F(x) is the bracket model, fk(x) is a single decision tree classifier, y is the result of a single decision tree bracket, and I(fk(x) = y) is the characteristic function. RFhas the advantages of high vaticination delicacy, fast training speed, strong resistance to noise and outliers, and generates training sets by arbitrary slice to reduce overfitting and ameliorate conception capability.

G. K-Nearest Neighbour

1) When a new sample x is input to the arbitrary branch, all decision trees (x) classify the new sample independently, and eventually determine by advancing the bracket results KNN is a popularsupervised literacy algorithm.
2) KNN is enforced bychancing the k closest training samples in thetraining set grounded on a certain distancemeasure, and also prognosticating grounded on the information of these k samples (where k is a positive integer).
3) Generally, a voting system is used in bracket tasks, where the most frequent order

$$Y = F(x) = argmax\ I(f(x) = y),$$

marker among these k samples is named as thevaticination result.

V. ACKNOWLEDGEMENT

We'd like to express our deep gratefulness to Mr. KRISHNA GUDI for his precious and formative suggestions during the planning and development of this design. His amenability to give his time so freehandedly has been veritably much appreciated. We'd also like to thank all the professors of KSIT for their nonstop support and stimulant.

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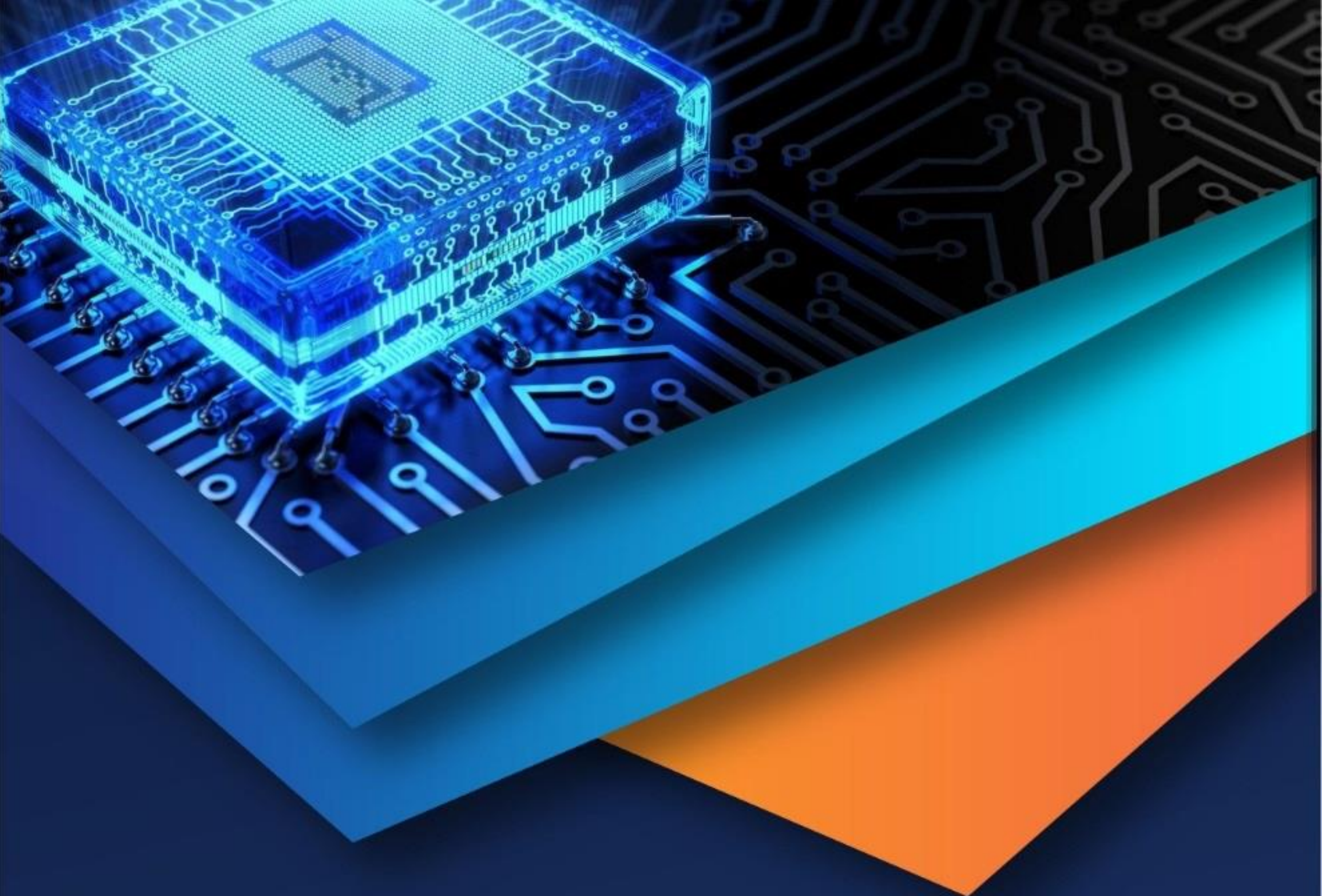

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