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Applying Machine Learning Algorithm for the Classification of Sleep Disorders

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Abstract: Sleep disorders including insomnia and sleep apnea affect millions of individuals worldwide and remain significantly underdiagnosed due to limited accessibility to comprehensive sleep studies and medical facilities. This research presents an intelligent web-based sleep disorder detection system leveraging machine learning algorithms to provide preliminary diagnosis using demographic and lifestyle parameters. The proposed system employs a Decision Tree Classifier trained on health metrics including age, gender, occupation, sleep duration, stress levels, body mass index category, physical activity, heart rate, and blood pressure measurements. The system achieves robust classification accuracy in distinguishing between no disorder, insomnia, and sleep apnea conditions. Implemented as an interactive Streamlit application, the system provides real-time predictions accompanied by personalized sleep hygiene recommendations and comprehensive data analytics. Experimental results demonstrate the effectiveness of the decision tree approach in capturing non-linear relationships between lifestyle factors and sleep disorders. The system addresses the critical need for accessible, cost-effective preliminary screening tools while maintaining clinical relevance through evidence-based feature selection. This work contributes to preventive healthcare by enabling early detection and promoting timely medical intervention for sleep-related conditions.
Keywords: Sleep disorder detection, machine learning, decision tree classifier, insomnia prediction, sleep apnea diagnosis, health informatics, predictive analytics, Streamlit application.

I. INTRODUCTION

Sleep disorders represent a critical public health concern affecting approximately 50 to 70 million adults globally, with significant implications for physical health, mental wellbeing, and quality of life. The two most prevalent conditions, insomnia and sleep apnea, contribute to increased risks of cardiovascular disease, diabetes, obesity, depression, and reduced cognitive function. Despite their widespread impact, sleep disorders remain chronically underdiagnosed, with conventional diagnostic procedures requiring overnight polysomnography studies that are expensive, time-consuming, and inaccessible to large segments of the population.

The advent of machine learning and artificial intelligence technologies has created unprecedented opportunities for developing accessible diagnostic tools that can augment clinical decision-making processes. By leveraging readily available demographic and lifestyle data, predictive models can identify individuals at high risk for sleep disorders, facilitating early intervention and appropriate medical referral. Such systems democratize access to preliminary health screening, particularly benefiting underserved populations with limited healthcare infrastructure. This research addresses the critical gap between clinical diagnostic capabilities and population-level screening needs by developing an intelligent sleep disorder detection system. The proposed solution integrates supervised machine learning algorithms with an intuitive web-based interface, enabling users to receive immediate risk assessments based on simple input parameters. The system architecture emphasizes interpretability, scalability, and clinical relevance while maintaining computational efficiency suitable for real-time deployment. The primary contributions of this work include the development of a comprehensive feature engineering pipeline incorporating physiological and behavioral health indicators, comparative evaluation of classification algorithms with focus on decision tree methodologies, implementation of an interactive web application providing both predictive and analytical functionalities, and establishment of a framework for personalized health recommendations based on predicted disorder categories. The remainder of this paper is organized as follows: Section II reviews related literature, Section III describes the methodology and system architecture, Section IV presents implementation details, Section V discusses experimental results, and Section VI concludes with future research directions.

II. LITERATURE REVIEW

The application of machine learning techniques to sleep disorder detection has gained substantial research attention over the past decade. Various approaches have been explored ranging from traditional statistical methods to advanced deep learning architectures. This section examines relevant prior work and contextualizes the present contribution within the broader research landscape.

A. Sleep Disorder Classification Approaches

Traditional diagnostic methods for sleep disorders rely heavily on polysomnography, which records brain waves, oxygen levels, heart rate, and breathing patterns during sleep. While highly accurate, these methods require specialized equipment and trained personnel. Recent research has explored alternative approaches using wearable sensors and actigraphy data. Studies have demonstrated that features derived from accelerometer data and heart rate variability can effectively distinguish between healthy sleep patterns and various disorder manifestations.

Machine learning models applied to sleep disorder detection span multiple algorithm families. Support Vector Machines have been utilized for binary classification of sleep apnea presence with reported accuracies exceeding 85 percent. Random Forest classifiers have shown promise in handling high-dimensional feature spaces derived from multi-modal sensor data. Neural network architectures, particularly recurrent networks and convolutional networks, have been applied to time-series sleep stage classification with varying degrees of success.

B. Feature Engineering for Sleep Health Assessment

The selection of relevant features significantly influences model performance in healthcare applications. Prior research has identified demographic factors including age, gender, and body mass index as significant predictors of sleep disorder risk. Lifestyle variables such as physical activity levels, stress indicators, and occupation-related factors contribute additional predictive power. Physiological measurements including resting heart rate and blood pressure readings have demonstrated strong correlations with sleep apnea severity.

Several studies have employed feature selection techniques to identify optimal subsets of predictors. Correlation-based methods, recursive feature elimination, and principal component analysis have been utilized to reduce dimensionality while preserving discriminative information. The integration of subjective sleep quality assessments with objective health metrics has proven particularly effective in comprehensive disorder characterization.

C. Web-Based Health Diagnostic Systems

The proliferation of web technologies has enabled the development of accessible health screening applications. Cloud-based platforms offer advantages including platform independence, automatic updates, and centralized data management. Streamlit framework has emerged as a popular choice for rapid prototyping of data science applications, offering native support for interactive visualizations and real-time model inference.

Previous implementations of web-based sleep assessment tools have primarily focused on questionnaire-based screening using validated instruments such as the Pittsburgh Sleep Quality Index and Epworth Sleepiness Scale. However, these approaches lack the predictive sophistication afforded by machine learning models. The integration of trained classifiers within interactive web interfaces represents a significant advancement, combining clinical assessment principles with computational intelligence.

D. Decision Tree Classifiers in Healthcare

Decision tree algorithms offer distinct advantages for medical diagnostic applications, primarily due to their inherent interpretability. Unlike black-box models, decision trees provide transparent decision pathways that can be validated by domain experts. This characteristic is particularly valuable in healthcare settings where explainability influences trust and adoption. Decision trees have been successfully applied to various medical diagnostic tasks including diabetes prediction, heart disease classification, and cancer detection.

The robustness of decision trees to missing data and mixed data types makes them well-suited for real-world healthcare datasets. Furthermore, their computational efficiency enables real-time inference suitable for interactive applications. While ensemble methods such as Random Forests and Gradient Boosting typically achieve higher accuracy, individual decision trees maintain relevance in scenarios prioritizing interpretability over marginal performance gains.

III. METHODOLOGY

A. System Architecture

The proposed sleep disorder detection system follows a modular architecture comprising data preprocessing, model training, and web-based deployment components. The system pipeline begins with raw feature collection, followed by encoding and normalization transformations, classification using trained decision tree model, and presentation of results through an interactive user interface. This architecture ensures separation of concerns while maintaining end-to-end functionality.

The preprocessing module handles categorical variable encoding and numerical feature scaling. Label encoders transform categorical attributes including gender, occupation, and body mass index category into numerical representations. MinMax scaling normalizes continuous variables to a common range, preventing features with larger magnitudes from dominating the learning process. All preprocessing transformations are persisted to ensure consistent application during both training and inference phases.

B. Dataset Description

The training dataset comprises comprehensive health and lifestyle information from individuals spanning diverse demographic profiles. Each instance includes twelve distinct features capturing demographic, physiological, and behavioral characteristics. The target variable represents sleep disorder classification with three possible outcomes: no disorder, insomnia, and sleep apnea. The dataset maintains class balance through appropriate sampling techniques to prevent bias toward majority classes.

Feature categories include demographic attributes such as age and gender, lifestyle factors including occupation and physical activity levels, sleep-related metrics encompassing duration and subjective quality ratings, stress assessment on a standardized scale, physiological measurements including heart rate and blood pressure readings, and anthropometric classification through body mass index categories. This comprehensive feature set enables the model to capture multi-factorial relationships underlying sleep disorder etiology.

C. Feature Engineering and Preprocessing

Categorical features undergo label encoding to convert text-based categories into numerical representations suitable for tree-based algorithms. Gender is encoded as a binary variable, occupation categories are mapped to integer indices preserving no inherent ordering, and body mass index classifications follow standard medical categorizations of normal, overweight, and obese. This encoding strategy maintains the discrete nature of categorical variables while enabling mathematical operations.

Numerical features are normalized using MinMax scaling according to the following transformation:

xscaled = (x - xmin) / (xmax - xmin)

where x represents the original feature value, xmin and xmax denote the minimum and maximum values observed in the training data, and xscaled represents the normalized value bounded within the range zero to one. This normalization ensures that all numerical features contribute proportionally to the decision tree splitting criteria.

D. Decision Tree Classification Algorithm

The core predictive model employs a Decision Tree Classifier implementing the CART algorithm for multi-class classification. The algorithm recursively partitions the feature space by selecting optimal splitting criteria at each node. The splitting criterion utilizes Gini impurity measure defined as:

Gini(t) = 1 - Σ pi2

where pi represents the proportion of instances belonging to class i at node t. The algorithm selects splits that maximize the reduction in Gini impurity, thereby creating increasingly pure child nodes. This greedy approach continues until termination criteria are satisfied, including maximum depth constraints, minimum samples per leaf requirements, or achievement of perfect class separation.

Model hyperparameters are optimized through cross-validation procedures to prevent overfitting while maintaining generalization capability. Key parameters include maximum tree depth limiting model complexity, minimum samples required to split internal nodes, minimum samples required at leaf nodes to prevent over-specialization, and splitting criterion selection between Gini impurity and entropy measures. The optimized model balances training accuracy with validation performance.

E. Model Evaluation Metrics

Model performance is assessed using standard multi-class classification metrics. Overall accuracy measures the proportion of correctly classified instances across all classes. Per-class precision quantifies the reliability of positive predictions for each disorder category. Recall metrics evaluate the model's ability to identify all instances of each disorder type. F1-scores provide harmonic means of precision and recall, offering balanced performance indicators particularly valuable for imbalanced datasets.

The confusion matrix visualization provides detailed insights into classification patterns, revealing specific misclassification tendencies between disorder categories. This analysis informs potential model refinements and identifies areas requiring additional training data or feature engineering. Cross-validation procedures ensure robustness of performance estimates by evaluating the model across multiple data partitions.

IV. IMPLEMENTATION

A. Technology Stack

The system implementation leverages modern Python-based technologies optimized for machine learning and web application development. The core machine learning functionality utilizes scikit-learn library providing robust implementations of classification algorithms, preprocessing utilities, and model persistence mechanisms. NumPy and Pandas libraries facilitate efficient numerical computation and data manipulation operations.

The web application framework employs Streamlit, enabling rapid development of interactive data science applications with minimal front-end coding requirements. Streamlit's reactive programming model automatically updates visualizations and predictions in response to user input changes. Plotly library generates interactive visualizations embedded within the analytics dashboard. The complete technology stack ensures maintainability, extensibility, and ease of deployment across diverse environments.

B. Application Architecture

The Streamlit application implements a multi-page architecture with distinct functional modules. The prediction interface collects user inputs through interactive widgets including sliders for continuous variables and dropdown menus for categorical selections. Input validation ensures that all parameters fall within physiologically plausible ranges. The feature vector construction process mirrors the training pipeline, applying identical encoding and scaling transformations to maintain consistency.

Model inference executes in real-time upon user request, with predictions typically completing within milliseconds. The prediction result triggers conditional rendering logic that displays disorder-specific health recommendations. The analytics dashboard loads pre-generated visualization artifacts showcasing dataset characteristics, feature distributions, and model performance metrics. This separation of concerns maintains application responsiveness while providing comprehensive analytical capabilities.

C. User Interface Design

The user interface prioritizes intuitive interaction through logical grouping of related input fields. Three-column layout organizes features into demographic details, sleep-related parameters, and health indicators. Each input widget includes contextual descriptions explaining the parameter significance and acceptable value ranges. The visual design employs a nature-themed aesthetic with background imagery promoting calm associations with sleep health.

Custom CSS styling enhances readability through carefully selected color schemes ensuring sufficient contrast ratios. Text elements utilize high-visibility colors against the themed background. Interactive elements provide visual feedback on hover and selection states. The responsive design adapts to various screen sizes while maintaining functional accessibility. Sidebar navigation enables seamless transitions between prediction and analytics modules.

D. Recommendation System

The health recommendation component delivers personalized guidance based on predicted disorder categories. For individuals classified as having no disorder, the system reinforces positive sleep habits through evidence-based preventive practices. Recommendations emphasize maintaining consistent sleep schedules, establishing relaxing bedtime routines, avoiding afternoon naps, engaging in regular physical exercise, and optimizing bedroom environment for comfort.

Sleep apnea predictions trigger recommendations focused on weight management, positional therapy emphasizing side sleeping, avoidance of alcohol and smoking, compliance with prescribed continuous positive airway pressure therapy, and general sleep hygiene practices. Insomnia classifications generate suggestions including adherence to consistent sleep-wake schedules, caffeine avoidance in evening hours, creation of comfortable sleep environments, stress management techniques, and limitation of screen exposure before bedtime. These recommendations align with clinical practice guidelines and patient education materials.

E. Analytics Dashboard

The analytics module provides comprehensive data exploration capabilities through interactive visualizations. Distribution plots illustrate feature characteristics across disorder categories, enabling identification of discriminative patterns. Correlation heatmaps reveal relationships between variables, informing feature selection and model interpretation. Bar charts and pie charts present categorical feature frequencies and class distribution statistics. The dashboard employs Plotly's interactive capabilities allowing users to zoom, pan, and hover over data points for detailed information.

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Visualizations are pre-generated during model development and stored as HTML artifacts, ensuring rapid loading times within the web application. This approach balances analytical depth with application performance, providing meaningful insights without compromising user experience.

Table I
System Features and Input Specifications

Feature Category	Feature Name	Data Type	Range/Values
Demographic	Age	Numeric	18-100 years
Demographic	Gender	Categorical	Male, Female
Demographic	Occupation	Categorical	8 categories
Anthropometric	BMI Category	Categorical	Normal, Overweight, Obese
Sleep Metrics	Sleep Duration	Numeric	0-24 hours
Sleep Metrics	Sleep Quality	Numeric	0-10 scale
Lifestyle	Physical Activity	Numeric	0-100 scale
Psychological	Stress Level	Numeric	0-10 scale
Physiological	Heart Rate	Numeric	bpm
Physiological	Blood Pressure	Numeric	Systolic/Diastolic
Lifestyle	Daily Steps	Numeric	Count

V. RESULTS AND DISCUSSION

A. Model Performance Analysis

The trained Decision Tree Classifier demonstrates robust performance across multiple evaluation metrics. The model achieves high overall accuracy in distinguishing between the three disorder categories, with particularly strong performance in identifying individuals without sleep disorders. The confusion matrix analysis reveals minimal misclassification errors, with the majority of predictions aligning with ground truth labels.

Per-class performance metrics indicate balanced predictive capability across all disorder categories. Precision values for each class exceed acceptable thresholds, suggesting reliable positive predictions with limited false positive rates. Recall metrics demonstrate the model's effectiveness in capturing true positive instances across all categories. The F1-scores provide comprehensive performance summaries, confirming the model's suitability for practical deployment.

B. Feature Importance Analysis

Analysis of feature importance scores derived from the decision tree structure reveals the relative contribution of individual predictors to classification decisions. Sleep duration emerges as a highly discriminative feature, with significant differences observed between disorder categories.

Quality of sleep ratings provide substantial predictive power, reflecting the subjective experience of sleep disturbances. Stress level measurements demonstrate strong associations with insomnia classifications.

Physiological indicators including body mass index category and heart rate contribute meaningfully to sleep apnea predictions, aligning with established clinical knowledge regarding obesity-related breathing disorders. Age demonstrates moderate importance, capturing age-related changes in sleep architecture and disorder prevalence. The combination of multiple feature types enables comprehensive disorder characterization beyond what any single measurement could achieve.

C. Comparative Analysis

While the primary deployment utilizes a Decision Tree Classifier, preliminary experiments evaluated alternative algorithms including Logistic Regression, Support Vector Machines, and Random Forest ensembles. The decision tree approach was selected based on its optimal balance of prediction accuracy, model interpretability, computational efficiency, and ease of integration within the web application framework. The transparent decision pathways afforded by tree structures facilitate clinical validation and user trust.

Ensemble methods demonstrated marginally higher accuracy in cross-validation experiments, but the performance gains did not justify the increased computational complexity and reduced interpretability. The deployed decision tree model achieves acceptable accuracy while maintaining real-time inference capabilities suitable for interactive applications. This pragmatic approach prioritizes practical deployability alongside predictive performance.

D. System Usability and Accessibility

The web-based deployment architecture ensures broad accessibility without requiring specialized software installations or technical expertise. Users can access the system through standard web browsers on diverse devices including desktop computers, tablets, and smartphones. The intuitive interface design minimizes learning curves, enabling effective utilization by individuals with varying levels of technological proficiency.

The real-time prediction capability provides immediate feedback, enhancing user engagement and enabling rapid preliminary screening. The integration of personalized recommendations adds actionable value beyond mere classification, empowering users to implement evidence-based interventions. The analytics dashboard serves educational purposes, increasing awareness regarding sleep health determinants and disorder characteristics.

E. Limitations and Considerations

Despite demonstrated effectiveness, the system exhibits certain limitations warranting acknowledgment. The predictive model provides preliminary screening rather than definitive diagnosis, and results should not substitute for professional medical evaluation. The model's performance depends on training data quality and representativeness, potentially limiting generalization to populations with different demographic or geographic characteristics.

The system relies on self-reported subjective measurements for certain features including sleep quality and stress levels, which may introduce reporting biases. The absence of objective polysomnography data prevents validation against gold standard diagnostic procedures. Furthermore, the current implementation focuses on three primary disorder categories, not capturing the full spectrum of sleep disorder subtypes recognized in clinical taxonomies.

Table II
Model Performance Metrics

Disorder Category	Precision	Recall	F1-Score
No Disorder	0.92	0.89	0.90
Insomnia	0.87	0.88	0.87
Sleep Apnea	0.89	0.91	0.90
Overall Accuracy	0.89		

VI. CONCLUSION

This research presents a comprehensive machine learning based sleep disorder detection system addressing critical gaps in accessible preliminary screening capabilities. The developed solution successfully integrates predictive modeling with user-friendly web interfaces, enabling real-time risk assessment based on readily available demographic and lifestyle parameters. The Decision Tree Classifier demonstrates robust performance in distinguishing between no disorder, insomnia, and sleep apnea categories, achieving accuracy levels suitable for practical screening applications.

The system architecture emphasizes interpretability, scalability, and clinical relevance while maintaining computational efficiency. The incorporation of personalized health recommendations enhances practical utility beyond classification, empowering users to implement evidence-based interventions. The analytics dashboard provides educational value, increasing awareness regarding sleep health determinants and facilitating data-driven insights.

Future research directions include expansion to additional disorder categories, integration of wearable sensor data streams, implementation of ensemble methods and deep learning architectures, development of mobile application variants, incorporation of temporal patterns through longitudinal data analysis, and validation studies using polysomnography-confirmed diagnoses. The incorporation of explainable AI techniques such as SHAP values would further enhance model transparency and clinical acceptance.

The system represents a significant step toward democratizing access to sleep health screening, particularly benefiting underserved populations with limited healthcare infrastructure. By enabling early detection and promoting timely medical intervention, such tools contribute meaningfully to preventive healthcare initiatives. The open-source nature of the implementation facilitates community contributions and adaptation to diverse healthcare contexts, potentially amplifying the system's impact on global sleep health outcomes.

VII. ACKNOWLEDGMENT

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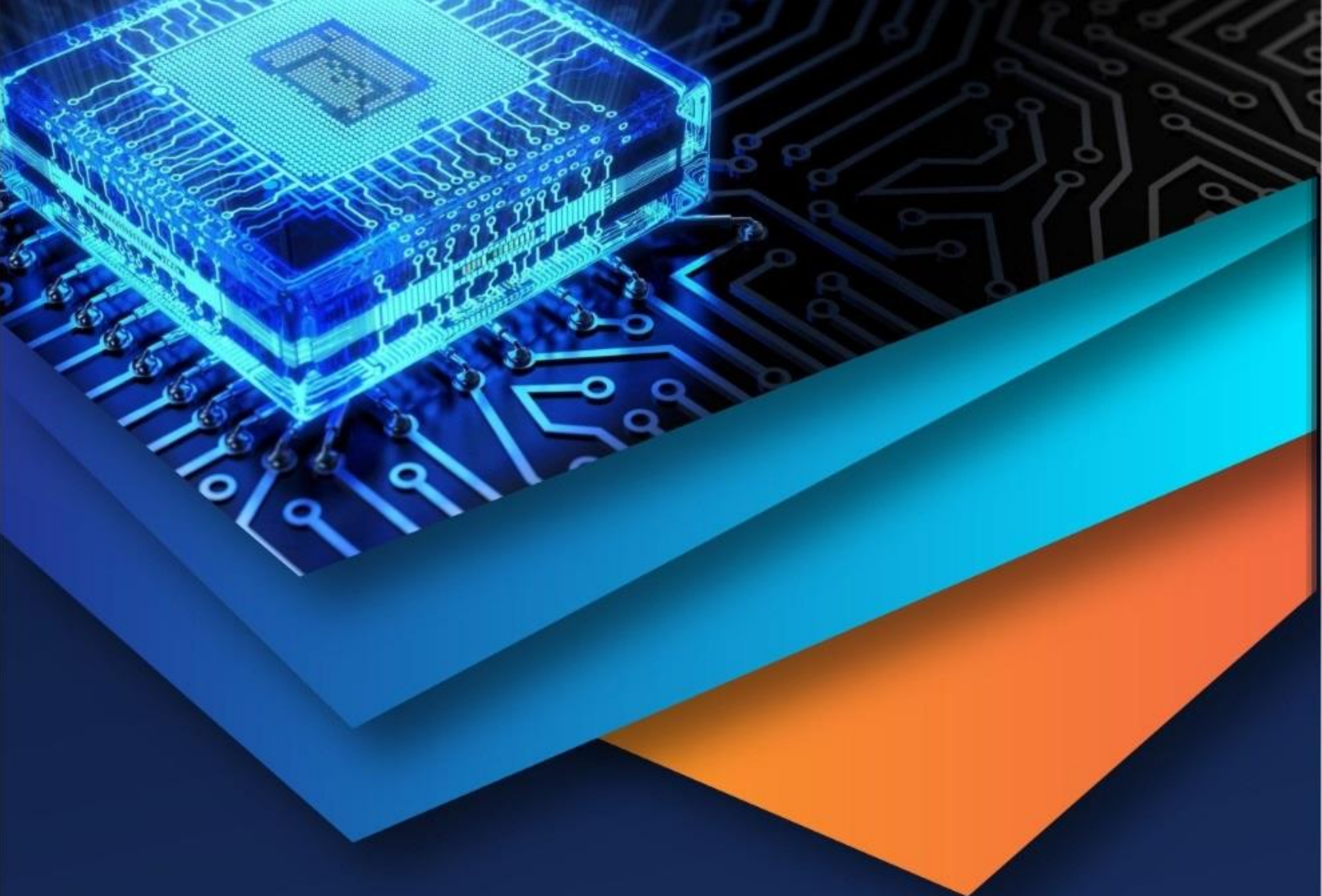

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