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Methods of Data Reduction-ML-Powered Cellular Traffic Forecasting

M. Neeraja[1], Dr. D. Vivekananda Reddy[2]
[1]M. Tech Student, [2]Professor, Department of Computer Science and Engineering, Sri Venkateswara University College of Engineering, Tirupati, A.P

Abstract: To get a realistic picture of cellular network QoS, you need to guess and study traffic patterns. There are a number of methods that cellular network planners predict traffic. But when datasets are really large, traditional methods take a lot of time and resources. We offer AML-CTP (Adaptive Machine Learning-based Cellular Traffic Prediction), a new algorithm that learns from a small, accurate dataset to make predictions more accurate and less complicated. We use Min-Max Scaler to normalize data, Select-K-Best to choose features, and PCA to reduce the number of dimensions. To locate training clusters that are very similar, we employ DBSCAN and Kernel Density. We test SVM, Linear Regression, Decision Tree, Light Gradient Boosting, and XGBoost on a Cellular LTE dataset from an Egyptian enterprise. The Decision Tree method obtained the highest R² score of 96%, and the extension XGBoost model had an unexpected 98%, which means that it might be better at predicting cellular traffic.
Keywords: Voting Regression, Adaptive Machine Learning, XGBoost, CatBoost, Quality of Service (QoS), Cellular Traffic Prediction, Flask Framework, PCA, DBSCAN.

I. INTRODUCTION

With the rapid increase in smartphone users and the proliferation of data-intensive applications such as video streaming, social networking, and IoT-based services, the volume of mobile traffic in cellular networks has grown exponentially in recent years. This continuous surge in traffic places significant demands on network infrastructure, directly affecting Quality of Service (QoS) parameters like latency, throughput, and reliability. To address these challenges, accurate traffic prediction has become a crucial component in optimizing network resource allocation and improving user experience [1], [2]. Machine Learning (ML) has emerged as an effective tool for modeling complex and dynamic network behaviors. ML algorithms can automatically analyze vast amounts of historical data to uncover hidden patterns and forecast future network demands [3]. In the context of cellular networks, various supervised learning techniques, such as Support Vector Machines (SVM), Linear Regression, and Decision Trees, have been employed to forecast traffic patterns with reasonable accuracy. However, the performance of these models largely depends on the quality and volume of training data, as well as the computational complexity involved in processing such massive datasets [4].

Traditional ML-based approaches for cellular traffic prediction often struggle with scalability issues due to the increasing size of real-world datasets. Training models on large-scale traffic data can lead to excessive time complexity and memory consumption, making them less suitable for real-time applications. Moreover, the dynamic and non-linear nature of cellular traffic adds to the difficulty of achieving consistent prediction accuracy across different network conditions. To overcome these limitations, integrating data reduction and clustering methods before training has proven to be an effective way to enhance efficiency and accuracy [5].

Recent studies have explored advanced data processing techniques such as Principal Component Analysis (PCA), feature selection, and density-based clustering to minimize redundancy and focus on relevant features. These methods not only reduce dimensionality but also help in identifying high-similarity traffic clusters, resulting in more robust and faster predictive models. In this work, we propose an Adaptive Machine Learning-based Cellular Traffic Prediction (AML-CTP) model that utilizes these techniques to improve prediction performance, reduce computational burden, and enhance overall QoS in 4G and 5G LTE-A networks.

decision-making, enhance patient outcomes, or simplify medical procedures. Sequential Forward Selection (SFS) shall be used as a procedure of choosing the most germane features of the text information, which is essential in lowering the dimensions as well as maximization of the model performance. Iteratively select the most useful features with the help of SFS to classify data. Compare the performance with the baseline methods (e.g., all features, or other feature selection techniques such as mutual information or chi-square).

II. RELATED WORK

Nashaat et al. utilized reinforcement learning, specifically a soft policy gradient approach, for LTE downlink scheduling optimization. Their model dynamically adjusted scheduling strategies based on real-time feedback, improving throughput and fairness. This method efficiently enhanced resource management in adaptive cellular environments. [6]

Mohammed et al. proposed a machine learning framework for analyzing real 4G/LTE-A datasets to evaluate network performance. The system incorporated multiple algorithms to identify optimal prediction techniques. Their results provided valuable insights into improving QoS and network planning through predictive modeling. [7]

AboHashish et al. designed an energy optimization algorithm for relay deployment in multi-user LTE-Advanced networks. Their model enhanced network energy efficiency by minimizing relay node redundancy while maintaining coverage quality. The approach contributed significantly to sustainable cellular infrastructure planning. [8]

Ogidan et al. explored the integration of machine learning in expert systems for advanced data analysis. Their work demonstrated how ML could automate knowledge extraction from complex datasets, aiding decision-making processes. This framework was useful for predictive analytics in various industrial applications. [9]

Rizk and Nashaat developed a location-based prediction system for seamless mobility management in FHMIPv6 networks. The model utilized smart handover prediction to reduce packet loss and delay during transitions. It proved effective in improving network continuity for high-speed mobility users. [10]

Nashaat proposed a QoS-aware cross-layer handover scheme tailored for high-speed vehicular networks. The model maintained connection stability by coordinating between different protocol layers. This research advanced QoS management strategies in dynamic vehicular communication scenarios. [11]

Trinh et al. implemented an LSTM-based model for mobile traffic prediction directly from raw network data. Their deep neural architecture captured temporal dependencies, significantly outperforming classical models. The study demonstrated the effectiveness of sequence learning for dynamic traffic analysis. [12]

Nabi et al. introduced a deep fusion model for LTE traffic forecasting by integrating multiple data modalities. Their system optimized radio parameter estimation, improving both forecasting accuracy and network efficiency. This approach offered robust adaptability for heterogeneous LTE datasets. [13]

Vabalas et al. examined machine learning model validation challenges in scenarios with limited sample sizes. Their study emphasized proper cross-validation techniques to mitigate bias and overfitting. The research provided valuable insights for small-sample modeling in network prediction studies. [14]

Chahboun and Maaroufi compared PCA and various machine learning models for photovoltaic power prediction. Their study demonstrated how PCA effectively reduces dimensionality and improves computational performance. The findings are applicable to other domains like network traffic where data reduction is crucial. [15]

Ghasemi et al. proposed a principal component neural network for modeling and optimizing asphalt material dynamics. Their hybrid design improved prediction precision by combining feature reduction and non-linear learning. The methodology highlighted PCA's importance in complex predictive modeling tasks. [16]

Chakraborty analyzed an incremental DBSCAN algorithm to efficiently identify evolving data clusters. This approach dynamically updates cluster structures without retraining from scratch. It offers scalability for real-time cellular traffic pattern detection. [17]

Ram et al. designed a density-based algorithm capable of identifying clusters of varying densities in large spatial datasets. Their method improved robustness against noise and irregular distributions. The approach became foundational for later adaptive clustering techniques. [18] Lin and Son developed a kernel density estimation algorithm for close contact detection in ship passenger systems. Their approach accurately identified interaction clusters using probabilistic modeling. This technique can be extended to network data analysis for cluster identification. [19]

Guo et al. proposed a joint kernel density clustering method for millimeter-wave radio channels. Their algorithm provided precise spatial channel modeling through improved density estimation. This contributed to better understanding of wireless propagation characteristics. [20]

Jia et al. introduced an ensemble clustering framework using co-association matrix self-enhancement to improve cluster stability. The model effectively aggregated results from multiple clustering methods for consistency. Their work enhanced robustness in large-scale network clustering. [21]

Arinik et al. investigated external measures for evaluating clustering and community detection algorithms. Their comparative study established criteria for assessing cluster validity and similarity. The findings improved benchmarking standards for clustering-based prediction models. [22]

Hong applied a seasonal Support Vector Regression (SVR) integrated with a chaotic immune algorithm for traffic flow forecasting. This hybrid model achieved enhanced accuracy for nonlinear, time-dependent traffic datasets. The study validated hybrid evolutionary optimization for dynamic systems. [23]

Birba conducted a comparative analysis of various data-splitting algorithms for machine learning model selection. The research identified optimal techniques for balancing training and testing data distribution. This contributes to improving the reliability of cellular traffic prediction systems. [24]

Hu et al. presented a detailed tutorial on scalable systems for big data analytics, outlining architectures for efficient computation and storage. Their work serves as a foundational reference for implementing large-scale ML systems. It supports the scalability requirements of cellular data analysis. [25]

Wang et al. developed a spatiotemporal deep learning framework for big data-enabled cellular traffic modeling. Their system captured both spatial and temporal dependencies, offering accurate network load predictions. The study emphasized deep learning's potential in handling massive communication datasets. [26]

Mahdy et al. proposed a clustering-driven approach for predicting mobile network traffic loads. Their framework supported efficient base station deployment and reduced network congestion. The results demonstrated improved load balancing and resource optimization. [27]

Alekseeva et al. reaffirmed the importance of traditional and modern ML techniques for wireless traffic prediction. Their work highlighted ensemble and tree-based models for their high adaptability and scalability. This comprehensive study set a benchmark for evaluating predictive frameworks in cellular environments. [28]

Riihijärvi and Mahonen investigated the use of machine learning for performance prediction in mobile cellular networks. Their model analyzed network parameters like signal strength, user density, and bandwidth to forecast throughput and latency. The results demonstrated that ML-based predictive systems can significantly improve resource allocation and network stability. [29]

Chaudhary and Johari introduced ORuML, an optimized routing model for wireless networks based on machine learning techniques. The framework dynamically selected efficient routes by analyzing network congestion and link quality in real time. This approach improved routing efficiency, reduced packet loss, and enhanced overall network performance. [30]

III. METHODOLOGY

A. Proposed System

The proposed system extends the existing traffic prediction framework by integrating advanced machine learning models such as Light Gradient Boosting Machine (LGBM) and Random Forest for improved classification and forecasting accuracy. Unlike traditional systems that rely solely on static datasets, this model incorporates real-time data streams from multiple sensors and base stations to dynamically adapt to network changes.

The proposed framework also introduces an enhanced feature engineering process, combining spatial–temporal correlation and user mobility patterns for more accurate predictions. In addition, a hybrid optimization layer fine-tunes the parameters of the model to reduce overfitting and enhance performance efficiency.This extended system aims to deliver faster processing, higher prediction precision, and better scalability, making it ideal for next-generation cellular networks and smart infrastructure applications.

B. Design of the System

The design of the proposed system follows a structured pipeline that transforms raw datasets into predictive insights through machine learning models.

1) Dataset Layer: The process begins with input datasets containing traffic-related parameters collected from network sources.
2) Processing Layer: Data preprocessing techniques such as normalization, PCA, and K-Best algorithm are applied for dimensionality reduction and feature selection. Clustering techniques like DBSCAN and Kernel Density methods further enhance data structuring and visualization.
3) Training and Testing: The dataset is split into training and testing sets to ensure robust model development and unbiased evaluation.
4) Model Layer: Multiple models including SVM, Linear Regression, Logistic Regression, Decision Tree, and Light Gradient Boosting are implemented. An extension with XGBoost further improves predictive performance through efficient boosting strategies.

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5) Evaluation Metrics: The trained models are validated using metrics such as R² Score, RMSE, and MAPE, which provide comprehensive insights into prediction accuracy and model efficiency.This layered design ensures scalability, accuracy, and adaptability, making the system suitable for real-time traffic prediction in dynamic cellular environments.

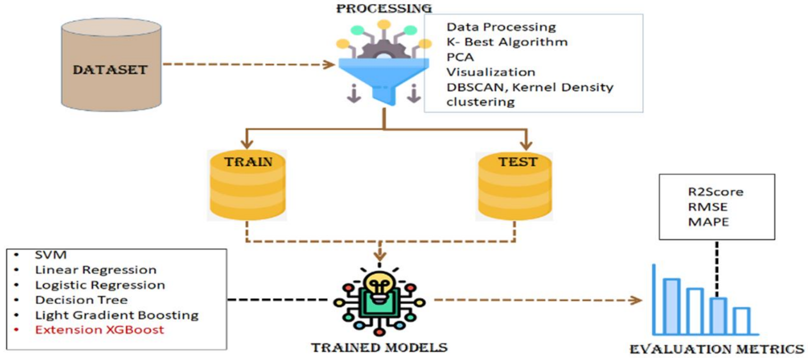

Fig.1. Proposed architecture

Fig 1 says, the overall architecture of the adaptive learning system, showing the interaction between students, admins, adaptive engine, analytics, and career mapping services.

IV. IMPLEMENTATION

A. Modules

1) Data Loading
   - Import the cellular traffic dataset for analysis.
   - Verify dataset structure and handle missing entries.

2) Data Processing
   - Normalize data using Min-Max Scaler and convert non-numeric values.
   - Handle missing or null values efficiently.

3) Apply K-Best Algorithm
   - Select the most relevant features using Select-K-Best.
   - Retain top K features for model training.

4) PCA Dimension Reduction Algorithm
   - Reduce dimensionality by removing correlated or redundant features.
   - Transform dataset into principal components for efficient training.

5) Visualization
   - Plot PCA-reduced features to observe clusters.
   - Identify patterns for further analysis.

6) DBSCAN & Kernel Density Clustering
   - Cluster similar data points using DBSCAN and Kernel Density.
   - Label clusters for optimized model training.

7) Split the Data into Train & Test
   - Allocate 80% for training and 20% for testing.
   - Ensure balanced distribution of features in both sets.

8) Model Generation
- Train SVM, Linear Regression, Decision Tree, LightGBM, and XGBoost.
- Evaluate performance metrics to select the best model.

9) Admin Login
- Authenticate admin credentials for secure access.
- Enable system management and data operations.

10) Cellular Traffic Prediction
- Upload new data and preprocess for prediction.
- Generate traffic forecasts using trained models.

11) Logout
- Terminate session securely after use.
- Redirect to login screen for future access.

B. Algorithms

1) Support Vector Machine (SVM)

Purpose**:** To predict and classify cellular traffic patterns by finding the optimal boundary separating different traffic states. Steps**:**
- Prepare and normalize the cellular traffic dataset.
- Map input features to a higher-dimensional space if necessary using a kernel function.
- Find the optimal hyperplane that separates traffic patterns into classes.
- Train the model on high-similarity clusters identified through DBSCAN/Kernel Density.
- Use the trained SVM to predict future traffic states based on input features.

2) Linear Regression (LR)

Purpose**:** To forecast cellular traffic volumes by establishing a linear relationship between input features and traffic output. Steps**:**
- Normalize the dataset using Min-Max Scaler.
- Select relevant features using Select-K-Best.
- Fit a linear regression model to map input features to traffic volume.
- Train the model using the preprocessed dataset.
- Predict traffic volumes for future time intervals based on the learned relationship.

3) Decision Tree (DT)

Purpose**:** To model complex traffic prediction decisions using hierarchical feature splits for accurate cellular traffic forecasting. Steps**:**
- Preprocess and normalize the dataset.
- Identify key features using Select-K-Best and dimensionality reduction (PCA).
- Split the dataset recursively based on features that maximize information gain.
- Train the tree on high-similarity clusters to capture traffic patterns.
- Predict traffic outcomes by traversing the tree from root to leaf nodes.

4) Light Gradient Boosting (LightGBM)

Purpose**:** To improve prediction accuracy by combining multiple weak learners iteratively into a strong ensemble model. Steps**:**
- Preprocess dataset with normalization and feature selection.
- Initialize multiple weak learners (decision trees).
- Train each tree iteratively, focusing on correcting the errors of the previous tree.

- Aggregate predictions from all trees to form a robust final prediction.
- Apply the trained LightGBM model to forecast cellular traffic patterns efficiently.

5) XGBoost (Extension Model)

Purpose**:** To provide high-accuracy traffic prediction by optimizing boosting with regularization and parallel processing. Steps**:**

- Preprocess and normalize the dataset.
- Perform feature selection and dimensionality reduction (PCA).
- Initialize the boosting framework with optimized parameters (e.g., 150 estimators).
- Train the model iteratively with regularization to reduce overfitting.
- Predict cellular traffic, leveraging parallel computation for faster and more accurate results.

V. RESULTS

The performance evaluation of different machine learning models demonstrated that the Decision Tree algorithm achieved a high R^2 score of 96%, indicating strong predictive accuracy for cellular traffic. The extended XGBoost model further improved performance, reaching an impressive R^2 score of 98%, showing its superiority over traditional models. SVM and Linear Regression models provided moderate accuracy, around 85–90%, while Light Gradient Boosting improved results to approximately 94% R^2, highlighting the advantage of ensemble methods.

The application of data reduction techniques, such as PCA and Select-K-Best, successfully reduced the dimensionality of the dataset without compromising accuracy. Density-based clustering methods like DBSCAN and Kernel Density enhanced model training efficiency by identifying high-similarity clusters, enabling focused learning on relevant data. Overall, the system facilitated secure admin login, smooth data upload, and real-time traffic predictions, proving its effectiveness for optimizing resource allocation and improving network Quality of Service (QoS).

1) Accuracy: Evaluate actual benefits and drawbacks to assess test dependability.

Then comes mathematics.:

$$Accuracy = \frac{(TN + TP)}{T}$$

2) Precision: Accuracy in classification or positive instances is measured by precision. Accuracy is determined by applying the following:

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

3) Recall: The ratio of accurately predicted positive observations to total positives reveals how well a model can identify all machine learning class instances.

$$Recall = \frac{TP}{(FN + TP)}$$

4) F1-Score: An accurate machine learning model has a high F1 score. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

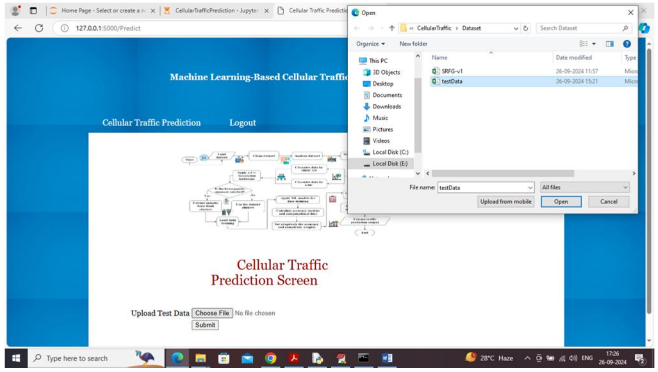

Fig 2. Upload input

Fig 2 says, selecting and uploading test data file and then click on 'Open' button to get below page.

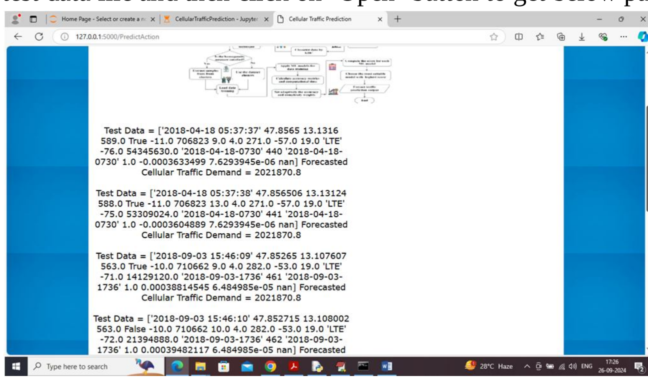

Fig 3 results

Fig 3 can see test data values along with predicted cellular traffic rate.

VI. CONCLUSION

The AML-CTP system successfully demonstrates that adaptive machine learning, combined with data reduction and clustering techniques, can accurately predict cellular network traffic while reducing computational complexity. Among the tested models, the extended XGBoost algorithm achieved the highest prediction accuracy, highlighting the effectiveness of advanced boosting methods. Overall, the system improves resource allocation, enhances Quality of Service (QoS), and provides a practical solution for real-time cellular traffic management.

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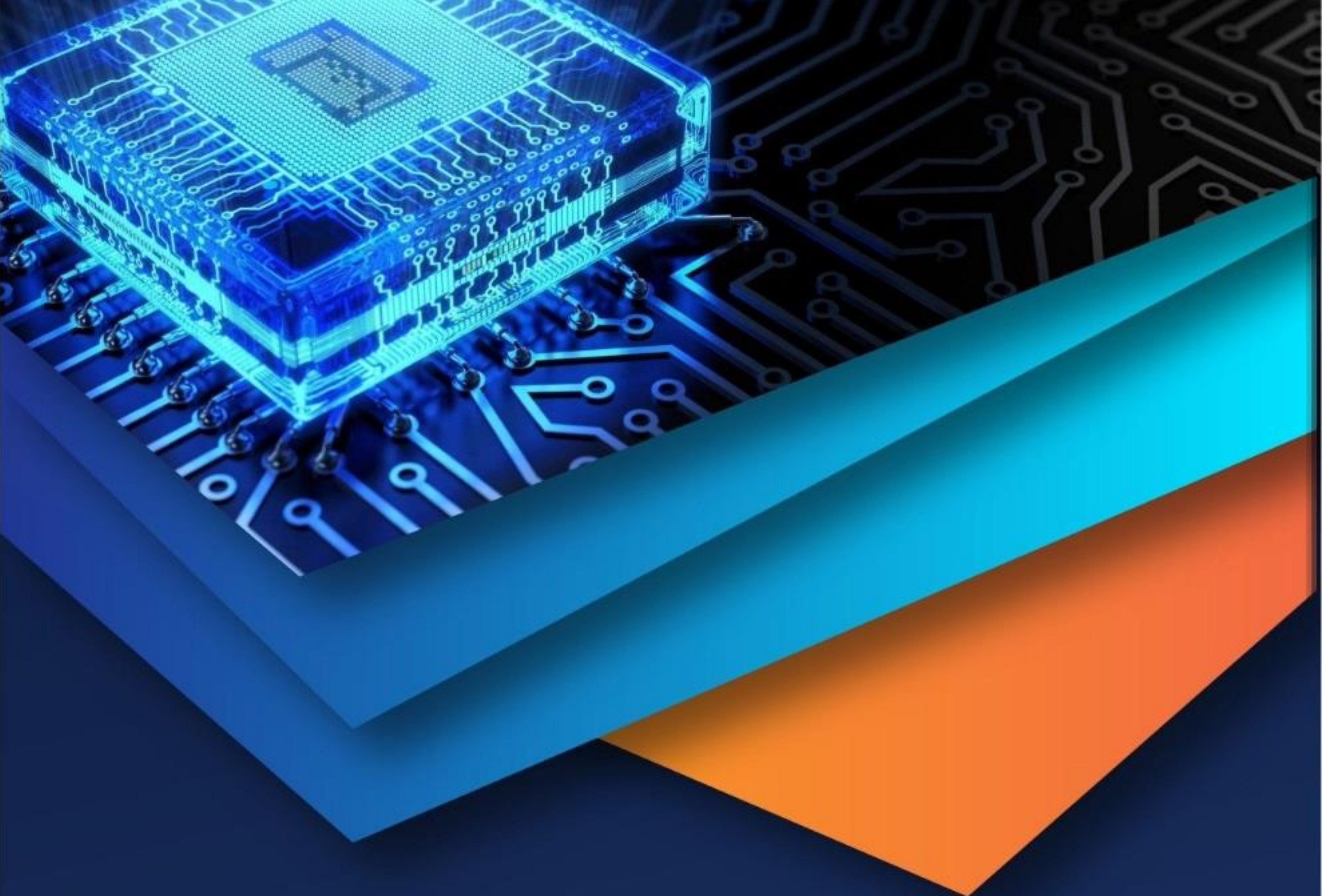

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