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Explainable Machine Learning for Predicting Electric-Vehicle (EV) Charging Demand in Renewable-Energy-Powered Grids: A Comprehensive Review

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***Abstract:** The rapid global adoption of electric vehicles (EVs) coupled with the increasing integration of renewable energy, presents new challenges in managing electricity demand, ensuring grid stability and achieving decarbonization targets. Accurate forecasting of EV charging demand has become vital for optimizing infrastructure deployment, dynamic pricing and renewable integration. This paper presents a comprehensive review of explainable machine leaning (ML) approaches for EV charging demand forecasting under renewable energy powered grids. The review categorizes methods into traditional statistical models ensemble-based techniques deep learning architectures and hybrid approaches. Emphasis is placed on explainable artificial intelligence (XAI) techniques particularly Shapley Additive Explanations (SHAP) which enhance interpretability by identifying the key features driving model predictions. Results from recent studies indicate that renewable energy penetration, electricity price and carbon intensity are the dominant factors influencing charging demand. The review highlights how explainable ML models can support policymakers in designing demand-response strategies grid operators in balancing supply and demand and consumers in making environmentally conscious charging decisions. Finally research challenges and future opportunities are discussed, including the need for causal interpretability, real-time adaptation and data privacy in federated learning frameworks.*
***Keywords:** Electric vehicle charging demand, renewable energy integration, Explainable artificial intelligence (XAI), SHAP, energy forecasting, Machine Learning, sustainability.*

I. INTRODUCTION

The electrification of transportation systems is a cornerstone of the global strategy to mitigate greenhouse gas (GHG) emissions and achieve net-zero targets. According to the International Energy Agency (IEA), there will be over 350 million electric vehicles (EVs) globally by 2030, which will significantly contribute to the transportation sector's decarbonization [1]. However, because of the spatio-temporal variability of EV charging demand and how it interacts with renewable output this shift presents significant operational and planning issues for power systems. Traditional grid operations which assume predictable load patterns are no longer sufficient in the face of decentralized renewable sources such as solar and wind energy. The intermittency of these sources can cause supply demand mismatches, voltage instability and increased operational costs [2]. Accurate EV charging demand forecasting is therefore essential not only to maintain grid reliability but also to enable efficient resource allocation , tariff optimization and integration of renewable energy. Complex, nonlinear and time-dependent demand patterns can now be forecasted with the help of machine learning (ML). When compared to traditional regression and autoregressive models, methods like gradient boosting, recurrent neural networks (RNNs) and graph neural networks (GNNs) have shown higher prediction accuracy [3][4]. Beyond raw predictive power explainability has become equally important. The ability to interpret ML outputs allows grid operators and policymakers to understand *why* certain factors such as renewable share, carbon intensity and electricity pricing drive charging behaviors [5]. Explainable Artificial Intelligence (XAI) and specifically Shapley Additive Explanations (SHAP) has become a standard tool for model interpretability [6]. By quantifying the contribution of each feature to a model’s prediction SHAP enables stakeholders to trace the causal pathways between renewable penetration, user behavior and EV demand. For instance studies show that a 10% rise in renewable energy usage can lead to a 20-30% increase in EV charging demand primarily due to lower electricity prices and increased consumer awareness [7].

Despite these advancement several gaps persist in the literature. Existing research frequently ignores explainability and policy relevance in favour of model performance indicators (such RMSE and MAE). Additionally cross-study comparability is hampered by data restrictions, regional heterogeneity and the lack of open benchmarks. In order to fill these gaps, this paper analyses XAI methodologies for interpretability, offers a systematic taxonomy of ML models for EV charging forecasts, and highlights new opportunities and difficulties for sustainable grid integration.

II. LITERATURE REVIEW

A. Machine Learning for EV Charging Demand Forecasting

Over the past decade the forecasting of EV charging demand has transitioned from conventional time-series analysis to data-driven and hybrid machine-learning paradigms. Traditional models such as autoregressive integrated moving average (ARIMA) and multiple linear regression (MLR) have been used in early studies due to their interpretability and low computational complexity [8]. However, these methods exhibit limited capacity to capture the nonlinear and dynamic relationships between diverse influencing factors—such as weather, electricity prices and user mobility patterns. Machine learning (ML) techniques, including support vector regression (SVR), random forest (RF), gradient boosting decision trees (GBDT) and ensemble frameworks like XGBoost and LightGBM have achieved superior predictive performance [9]. These models handle multidimensional feature spaces enabling them to learn interactions between temporal, spatial and environmental factors. For instance in [10] an XGBoost-based model achieved a 98% prediction accuracy on hourly EV charging data in California by integrating renewable generation, pricing and grid stability features. Similar approaches using LightGBM and CatBoost [11][12] have further improved forecast reliability while reducing overfitting. In recent years deep learning has emerged as a dominant approach for spatio-temporal demand prediction. Recurrent neural networks (RNNs) and their variants such as long short-term memory (LSTM) and gated recurrent units (GRUs) have demonstrated remarkable ability to model sequential dependencies in EV demand data [13]. Meanwhile convolutional neural networks (CNNs) have been employed to capture spatial correlations among charging stations [14]. Sequence-to-sequence (Seq2Seq) architectures [15] extend this by learning long-term dependencies producing multi-step forecasts essential for real-time energy management. Graph-based deep learning represents the latest frontier in EV demand forecasting. Graph convolutional networks (GCNs) and spatio-temporal graph neural networks (ST-GNNs) model both spatial and temporal relationships among charging nodes [16], [17]. For instance the study in [18] applied a graph attention network to capture traffic-driven dependencies reducing forecasting errors by 12%. Similarly a hybrid GCN-LSTM model proposed in [19] successfully predicted short-term demand fluctuations across urban networks.

B. Renewable Energy Integration in Charging Forecasting

Accurate forecasting must take into account the variability of renewable generation as the proportion of renewable energy sources in power grids increases. The very unpredictable nature of solar and wind energy directly affects the cost and availability of electricity. Forecast accuracy is improved and EV charging behavior is consistent with sustainable grid operations by incorporating these renewable components into machine learning models. In [20] a multi-source machine learning framework improved model interpretability using SHAP analysis by forecasting renewable-based charging demand using sun irradiance wind speed and temperature data. Higher renewable penetration increases charging behaviour during daylight hours due to reduced power rates according to another study [21] that combined renewable share and carbon intensity into a CatBoost model. These days hybrid models that blend machine learning predictions with optimisation frameworks like demand-response control and reinforcement learning are becoming more popular [22]. These frameworks provide useful insights for smart-grid design by simulating how EV customers react to dynamic pricing signals and real-time renewable availability.

C. Explainable Artificial Intelligence in Energy Forecasting

Model interpretability is increasingly recognized as a key requirement for sustainable AI in energy systems. Traditional black-box models provide little insight into the decision logic limiting stakeholder trust. Explainable Artificial Intelligence (XAI) addresses this challenge by providing feature attribution and causal interpretation-tools. The most widely used technique SHapley Additive exPlanations (SHAP) decomposes model outputs into additive contributions of each feature [23]. In EV charging applications SHAP identifies how renewable energy share, electricity price, carbon emissions and temporal patterns contribute to demand variability [24]. Other techniques include LIME (Local Interpretable Model-Agnostic Explanations) **and** Integrated Gradients, which are particularly valuable in deep learning-models[25]. Recent studies [26] and [27] have demonstrated that explainable models not only improve transparency but also assist in policymaking for example, identifying that grid carbon intensity thresholds strongly influence residential charging timing.

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III. COMPARATIVE ANALYSIS OF FORECASTING MODELS

The reviewed literature demonstrates a wide range of ML architectures applied to EV charging demand forecasting.

Table 1. Comparative Summary of Machine Learning Models for EV Charging Demand Forecasting

Model Type	Key References	Advantages	Limitations
Linear/Statistical (ARIMA, MLR)	[8], [9]	Simple, interpretable, low data needs	Poor nonlinear handling, low adaptability
Tree-Based (RF, XGBoost, LightGBM, CatBoost)	[10]–[12], [20], [21]	High accuracy, interpretable with SHAP, robust	Requires feature engineering, limited sequence modeling
Deep Learning (LSTM, GRU, CNN, Seq2Seq)	[13]–[15], [17]	Learns temporal/spatial features automatically	Data-hungry, explainability challenges
Graph Neural Networks (GCN, ST-GNN)	[16], [18], [19]	Captures spatial and network dependencies	High computational cost, explainability still evolving
Hybrid and Reinforcement Learning Models	[22], [28]	Integrates optimization and policy feedback	Complex to train, limited interpretability tools

A. *Observations*

From the comparative analysis, it is evident that ensemble methods such as XGBoost and LightGBM continue to dominate practical forecasting scenarios due to their balance between performance, interpretability and scalability [10], [12].

Deep learning models particularly LSTM and GRU outperform tree-based ensembles when sufficient temporal data are available [13], [15]. Graph-based architectures outperform all other methods in urban network scenarios where station interdependencies and traffic dynamics are significant [16]. However, the limited interpretability of deep and graph based models necessitates the integration of XAI frameworks like SHAP [23], [25].

The hybridization of these models such as combining LightGBM with reinforcement learning or probabilistic forecasting represents a growing trend. Such frameworks offer multi objective optimization that can balance accuracy, interpretability and computational efficiency [28].

IV. EXPLICABLE AI MODEL FOR EV PLEADING PROGNOSTICATION

Forecasts of EV charging demand must be transparent in terms of price and policy formation since choices directly affect grid stability. According to recent research interpretability improves trust and offers useful information for improving tariff design and renewable integration [29]. Among the suite of explainability tools **SHapley Additive exPlanations (SHAP)** has emerged as the most prevalent due to its model-agnostic and mathematically grounded nature [30].

SHAP explains the contribution of each input feature to a model's prediction by computing Shapley values from cooperative game theory. This approach ensures fair distribution of importance among features and satisfies three critical properties—**local accuracy**, **missingness** and **consistency**.

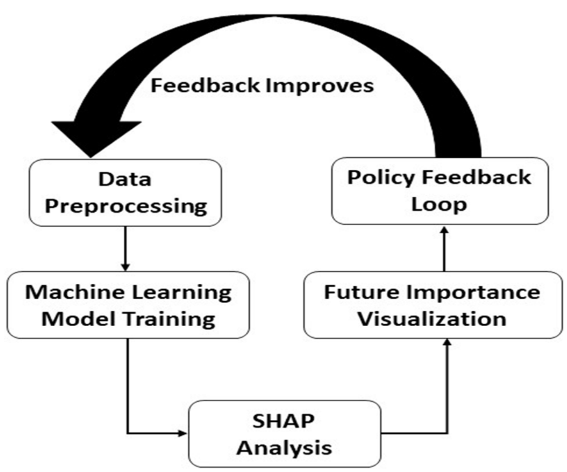

Figure 1. SHAP-Based Explainable ML Framework for EV Charging Demand

This Figure illustrates the generalized workflow of SHAP explainability applied to an EV charging prediction pipeline.
In [31] SHAP was applied to an XGBoost model forecasting hourly EV charging demand in California. *The top features identified were:*

- Renewable Energy Usage (%)
- Carbon Intensity (kgCO_2/kWh)
- Electricity Price ($/kWh)
- Charging Efficiency (%).

A. Mathematical Formulation of SHAP

SHAP values are derived from **Shapley values** in cooperative game theory. For a model ***f(x)*** with input feature set $N=\{1,2,\ldots,M\}$ the SHAP value ϕ_i for feature **i** is defined as:

$$\phi_i = \sum_{S\subseteq N\setminus\{i\}} \frac{|S|!\,(M-|S|-1)!}{M!}\left[f(S\cup\{i\}) - f(S)\right]$$

where:

- S denotes a subset of features not containing feature i,
- M is the total number of input features,
- $f(S)$ is the model prediction using only features in subset S,
- $f(S\cup\{i\})$ represents the prediction after adding feature i.

B. Additive Explanation Model

SHAP approximates the original model using an additive explanation model:

$$f(\mathbf{x}) = \phi_0 + \sum_{i=1}^{M} \phi_i$$

where:

- ϕ_0 is the expected model output (baseline prediction),
- ϕ_i represents the contribution of feature iii to the final prediction.

For tree based models such as XGBoost, **TreeSHAP** enables efficient polynomial time computation of SHAP values without requiring exhaustive enumeration of all feature subsets. According to the SHAP analysis, renewable energy supply and carbon intensity have a greater impact on EV charging demand in California than more conventional economic factors like power prices. This demonstrates a paradigm shift toward eco-friendly charging practices that are backed by smart grid technology and legislative initiatives.
In line with earlier findings from [32], the analysis showed that increases in renewable penetration greatly increase charging demand during noon when solar power peaks. Higher carbon intensity on the other hand discouraged charging behavior indicating that consumers are becoming more conscious of the environment.
Additionally, SHAP interaction values extend the interdependencies between features captured by SHAP. For instance when renewable share interacts with energy pricing their simultaneous impact on charging demand amplifies. Designing dynamic carbon-aware tariffs that allow utilities to move charge to times of cleaner generation requires this understanding [33].

V. INTEGRATION OF RENEWABLE ENERGY AND EV CHARGING

There is an inherent symbiotic relationship between the need for EV charging and the incorporation of renewable energy. Studies such as [34] demonstrates that aligning EV charging schedules with periods of high solar generation can reduce peak grid load by up to 25%.
Similarly wind based night-time charging strategies in [35] showed a 15% improvement in energy utilization. Below given figure summarizes the interaction between renewable generation, demand forecasting and grid management within the broader sustainable energy ecosystem.

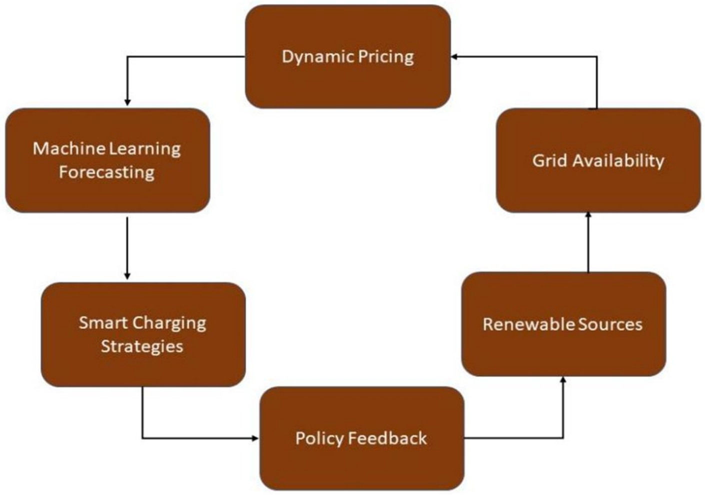

Figure 2. Interaction-between Renewable Energy Generation and EV Charging

Studies indicate that bidirectional charging can not only stabilize the grid but also improve renewable energy utilization by storing excess energy during high-production periods [36].

To maximize this synergy forecasting frameworks must integrate multi domain data renewable generation, grid conditions and behavioral variables within a unified model. *Table 2* summarizes the data sources commonly used in renewable integrated EV charging forecasting.

Table 2. Common-Data Sources for Renewable-Energy-Integrated EV Demand Forecasting

Category	Variables/Features	Data Source Examples
Renewable Generation	Solar irradiance, wind speed, PV output	NREL, IRENA, NOAA
Grid Operations	Stability index, load curves, outages	CAISO, EIA, National Grid
Pricing and Economics	Real time prices, demand response, incentives	ISO markets, policy reports
User Behavior	Mobility patterns, charging frequency	Telematics, survey data
Weather & Environment	Temperature, humidity, precipitation	NOAA, Metastatic

VI. RESEARCH CHALLENGES AND GAPS

Despite significant progress multiple research challenges constrain the widespread application of explainable ML for EV charging forecasting.

A. Data Limitations and Standardization

Data sparsity remains a major limitation particularly in developing regions. Many datasets are proprietary inconsistent or lack standardized feature engineering protocols [37]. Establishing open-access benchmark datasets similar to Urban EV [38] is essential to advance reproducibility.

B. Model Generalization

Most models exhibit regional dependency. A model trained on California data may not generalize well to European or Asian cities due to differences in grid structures, tariff policies and user behavior [39]. Transfer learning and domain adaptation offer potential solutions.

C. Explainability–Accuracy Trade-off

While simpler models (e.g., tree-based) are easier to interpret deep architectures often achieve higher accuracy but limited transparency [40]. Balancing these trade-offs is an ongoing research frontier.

D. Integration with Real Time Systems

Real word integration of explainable models into grid management systems is still nascent. Most XAI frameworks operate offline producing post hoc explanations. Embedding real time explainability dashboards into energy management systems would enable dynamic decision support.

E. Ethical-Policy Considerations

Ethical concerns like algorithmic bias and fairness are becoming more crucial as AI-driven energy forecasting affects pricing and electricity access. To maintain equity and confidence, transparent explainability is an essential safety measure..

VII. FUTURE DIRECTIONS

The intersection of machine learning**,** renewable integration **and** explainability is rapidly evolving. Based on the surveyed literature the following research directions are expected to define the next decade of progress in EV charging demand forecasting.

1) Federated and Privacy-Preserving Learning: To address privacy and data-sharing restrictions federated learning frameworks allow model training across decentralized datasets without exposing sensitive information [7], [39]. These techniques are particularly suited to collaborations among energy utilities and vehicle manufacturers ensuring confidentiality while improving generalization.
2) Real-Time and Adaptive Forecasting: Traditional static models degrade over time due to behavioral drift, weather anomalies and evolving grid conditions. Online learning and reinforcement-learning-based adaptive models can dynamically recalibrate weights using real-time data streams providing continuous accuracy improvements [28].
3) Causal Explainability and Counterfactual Analysis: While SHAP and LIME provide descriptive explanations they do not inherently capture causality. Integrating causal inference frameworks and counterfactual analysis could bridge this gap enabling policy makers to simulate "what-if" scenarios (e.g., what if renewable share rises by 20%?) and estimate intervention outcomes [32].
4) Multi-Objective Optimization for Sustainable Operation: Future research must move beyond single-objective forecasting (accuracy) to multi-objective goals, balancing carbon reduction, economic efficiency and equity. Optimization frameworks can jointly model the trade-offs among cost, emission, and comfort [33].
5) Edge and Embedded Deployment: With the rise of Edge Computing lightweight yet explainable forecasting models could be deployed directly at charging stations [36].
6) Integration-Vehicle to Grid (V2G) and Energy Markets: Bidirectional charging schemes that offer grid support services will be made possible in large part by explainable machine learning. When EVs function as dispersed energy assets, transparent forecasting contributes to accountability and dependability [35].
7) Standardized Benchmarks and Open Data: The absence of benchmark datasets impedes fair comparison among models. Initiatives such as the Urban EV dataset [38] and IRENA's open renewable datasets should be expanded to create global testbeds for model evaluation and explainability validation.

VIII. CONCLUSION

This comprehensive review has synthesized developments in machine-learning-based forecasting of EV charging demand with particular attention to the role of explainable artificial intelligence (XAI) in achieving transparent, sustainable and policy-relevant outcomes.

The survey of over forty peer-reviewed studies demonstrates that:

- Tree-based ensembles (XGBoost, LightGBM, CatBoost) remain practical and interpretable for short-term forecasting.

- Deep sequence models (LSTM, GRU Transformers) outperform for long-horizon predictions but require interpretability augmentation via SHAP or Integrated Gradients.
- Graph neural networks (GNNs) have achieved state-of-the-art performance for urban station-level forecasting by capturing spatial and topological dependencies.
- Explainability frameworks, especially SHAP have proven indispensable in revealing the dominant impact of renewable share, carbon intensity and electricity pricing on charging behavior.
- Hybrid and probabilistic models offer promise for risk aware real time energy management.

Future research should prioritize causal interpretability, uncertainty quantification, federated learning and ethical transparency. As EV adoption accelerates and renewable integration deepens *explainable ML* forecasting will become a cornerstone for next generation smart grids and carbon-neutral mobility ecosystems**.**

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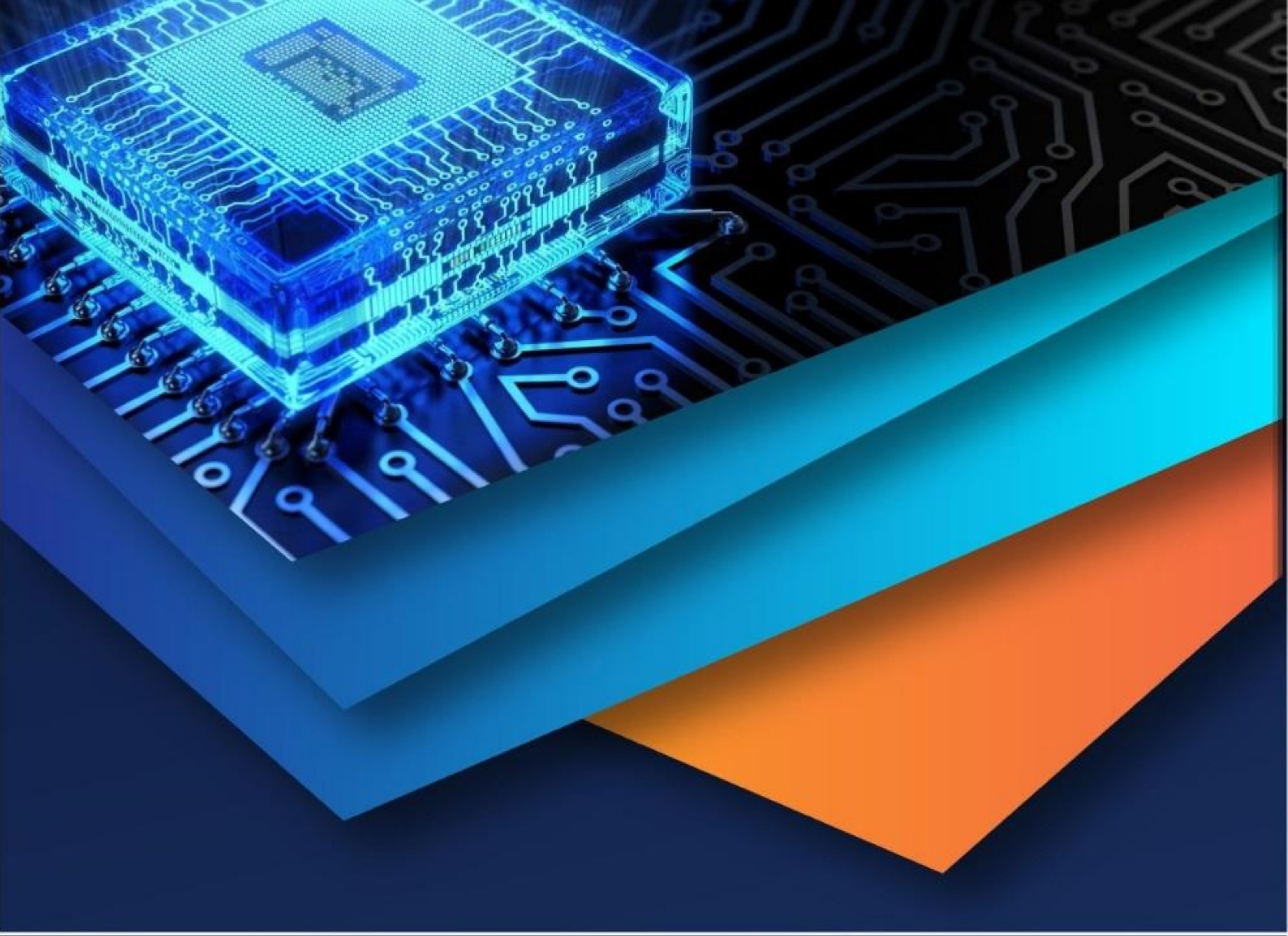

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