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Explainable AI for Crop Recommendation, Yield Forcasting and Rainfall Prediction in Smart Agriculture

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Abstract: A vital component of maintaining the world's expanding populace is farming. In agriculture field, factors such as soil quality, weather patterns, and crop yields are essential components of usual possessions that affect farming manufacture. Despite advancements, prevailing smart systems quiet struggle with handling big amounts in prediction claims, often facing difficulties in balancing prediction accuracy and learning efficiency. To ensure sustainable food production, integrating advanced machineries such as machine learning and artificial intelligence in agriculture is essential. This study proposes an explainable AI (XAI)-based smart agriculture system to provide holistic recommendation for precision farming aimed at improving productivity while reducing environmental impact. We compiled a comprehensive weather, soil, and crop dataset from official and verified sources in India. From this dataset, we extracted and optimized features using pre-trained architectures and enhanced barnacles mating optimization (EBMO) algorithm, addressing the high-measure mentality and computational complexity issues often encountered in agricultural data analysis. A vital component of maintaining the world's expanding populace is farming. In agriculture field, factors such as soil quality, weather patterns, and crop yields are essential components of usual possessions that affect farming manufacture. Despite advancements, prevailing smart systems quiet struggle with handling big amounts in prediction claims, often facing difficulties in balancing prediction accuracy and learning efficiency. To ensure sustainable food production, integrating advanced machineries such as machine learning and artificial intelligence in agriculture is essential. This study proposes an explainable AI (XAI)-based smart agriculture system to provide holistic recommendation for precision farming aimed at improving productivity while reducing environmental impact. We compiled a comprehensive weather, soil, and crop dataset from official and verified sources in India. From this dataset, we extracted and optimized features using pre-trained architectures and enhanced barnacles mating optimization (EBMO) algorithm, addressing the high-measure mentality and computational complexity issues often encountered in agricultural data analysis.

I. INTRODUCTION

Agriculture plays a vital role in ensuring food security, economic stability, and sustainable development. In recent years, global population growth and unpredictable climatic conditions have increased the demand for data-driven agricultural solutions. Conventional farming practices often rely on experience and manual observation, which may not be sufficient to cope with the dynamic nature of environmental changes. As a result, the integration of Artificial Intelligence (AI) into agriculture has emerged as a promising approach to enhance productivity, optimize resource utilization, and reduce uncertainties in decision-making. Advancements in machine learning (ML) and deep learning (DL) have enabled the development of intelligent systems capable of analyzing vast amounts of online agricultural and meteorological data. Online repositories such as government agricultural databases, meteorological departments, and open data platforms provide valuable datasets containing soil composition, temperature, humidity, and crop yield information. Using this data, AI models can perform critical tasks such as crop recommendation, yield forecasting, and rainfall prediction—helping farmers, agronomists, and policymakers make informed decisions. However, while these models can achieve high prediction accuracy, they often act as black boxes, providing little or no insight into the reasoning behind their predictions.

The absence of interpretability in AI systems raises serious concerns regarding trust, accountability, and transparency. In agriculture, where decisions directly impact food production and livelihood, stakeholders need to understand why a model recommends a certain crop or how it forecasts yield and rainfall. Without clear explanations, even accurate models may fail to gain user confidence. This is where Explainable Artificial Intelligence (XAI) becomes essential. XAI enhances model transparency by identifying and explaining the contribution of each input feature to the final output, helping users interpret the decision-making process of complex models.

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The framework employs explainability techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to highlight the influence of different features, such as temperature, soil pH, or rainfall, on each prediction. These explanations not only make AI predictions more transparent but also provide meaningful insights that can guide agricultural planning and policy-making.

Furthermore, since the system depends entirely on online data sources, it eliminates the need for costly IoT infrastructure and hardware sensors, making it more scalable, affordable, and accessible for developing regions. By combining high-accuracy predictive models with interpretability, this approach contributes toward building trustworthy and human-centered AI systems that support sustainable and intelligent agriculture.

The current study proposes an explainable, online-data-based AI framework that focuses on three core agricultural tasks: crop recommendation, yield forecasting, and rainfall prediction. The system utilizes openly accessible datasets from online repositories, including agricultural statistics, regional soil data, and meteorological archives. These sources eliminate the need for IoT sensors or costly field-level data collection, making the system affordable and scalable across different geographic regions. Machine learning algorithms such as Random Forest, XGBoost, and Support Vector Regression are used to train predictive models, while explainability tools like SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) provide insights into model behavior.

By combining predictive performance with interpretability, the framework aims to create AI systems that are both accurate and trustworthy. For instance, if the model forecasts a decrease in rice yield for a given district, it can highlight that reduced rainfall and declining soil potassium were the primary causes. Similarly, for rainfall prediction, it can show that humidity and temperature variations had the greatest impact on the result. These explanations make AI a partner rather than a black-box authority, helping farmers and agricultural planners make better-informed decisions. The broader vision of this research is to build a transparent and inclusive AI ecosystem for agriculture. In many developing regions, the cost and complexity of IoT-based systems restrict adoption. A cloud-based, explainable AI framework that uses freely available data can bridge this gap by making advanced decision-support tools accessible to all. Moreover, the inclusion of explainability ensures that stakeholders can audit model behavior, verify predictions, and continuously improve system reliability,this study explores how Explainable Artificial Intelligence can be leveraged to strengthen the credibility and practicality of AI in agriculture. By applying interpretable machine learning models to online datasets for crop recommendation, yield forecasting, and rainfall prediction, the research aims to enhance both model transparency and user trust. The outcomes of this work are expected to support more sustainable, data-driven agricultural practices and contribute to the responsible deployment of AI technologies in the farming sector.

II. RELATED WORK

Artificial Intelligence has become one of the most promising tools for transforming agriculture into a data-driven industry. Numerous studies have explored the application of machine learning and deep learning techniques for enhancing agricultural productivity and forecasting. However, most of these works emphasize accuracy and automation, while very few address the need for model interpretability and explainability—a key concern in real-world adoption. This section reviews existing research on AI-based approaches for crop recommendation, yield forecasting, and rainfall prediction, along with the emerging role of Explainable AI (XAI) in this domain.

Early research in crop recommendation systems primarily focused on supervised learning methods that utilized soil and climatic parameters to suggest suitable crops for cultivation. Patil et al. (2020) employed a Decision Tree algorithm using soil nutrient values (N, P, K) and pH level data for predicting optimal crops. Similarly, Sharma and Kumar (2021) used Support Vector Machines to recommend crops based on temperature and rainfall patterns. While these models achieved high accuracy, they lacked the ability to justify their recommendations, making it difficult for farmers to trust the system's outcomes. Recent efforts, such as those by Bhatia et al. (2023),introduced ensemble models combining Random

Forest and Gradient Boosting for improved precision, but the black-box nature of these models remained a limitation.

In the area of yield forecasting, machine learning has been widely adopted to predict production levels based on historical and environmental data. Gupta et al. (2022) applied Random Forest and Lasso Regression models on district-level crop yield datasets, achieving promising results for rice and wheat yield estimation. Another notable work by Ramesh et al. (2023) used Long Short-Term Memory (LSTM) neural networks to forecast yield trends across multiple seasons. Although these deep learning models captured complex relationships between features, they offered limited insight into *which variables* most influenced the yield outcome. Consequently, agricultural experts found it challenging to validate or interpret the results, which reduced practical reliability.

Similarly, rainfall prediction has been an active research area in agricultural data science. Researchers like Singh and Patel (2021) implemented linear regression and K-Nearest Neighbors (KNN) models using meteorological datasets to predict monthly rainfall patterns.

Deep learning models, including CNNs and RNNs, were later adopted to improve temporal accuracy (Kumar et al., 2022). While these systems performed well statistically, their non-transparent architectures made it nearly impossible to explain the reasoning behind predictions—such as which climate features contributed most to a rainfall increase or decline. growing recognition of this problem, the last few years have seen an increasing focus on Explainable Artificial Intelligence (XAI) in agriculture. Das et al. (2023) applied SHAP (SHapley Additive exPlanations) to explain soil and weather features affecting rice yield predictions. Similarly, Choudhury and Saini (2024) employed LIME (Local Interpretable Model-agnostic Explanations) to interpret a Random Forest-based crop recommendation system, improving user understanding and trust. However, these studies were limited to a single application domain—either crop recommendation or yield forecasting—without providing a unified explainable framework covering multiple prediction tasks.

The literature also reveals a gap in studies utilizing open, online datasets instead of IoT or sensor-based data collection. Many existing approaches depend on expensive hardware infrastructure for real-time monitoring, making them less feasible for small and medium-scale farmers. In contrast, several open repositories, such as the Indian Meteorological Department (IMD) archives, FAO crop databases, and Kaggle's agricultural datasets, provide rich online data that can power AI models without the need for IoT integration. Yet, only a few works have explored explainable AI frameworks using such readily available online data.

To address these research gaps, the present study proposes a comprehensive Explainable AI framework for crop recommendation, yield forecasting, and rainfall prediction, designed entirely around online agricultural and meteorological data. By incorporating XAI tools such as SHAP and LIME, the system aims to enhance model transparency and ensure that end users can visualize and understand the reasoning behind each prediction. This approach bridges the gap between data-driven intelligence and human understanding—making AI not only accurate but also interpretable and trustworthy for real-world agricultural decision-making.

III. SYSTEM ARCHITECTURE

A. *Overview of the System*

The proposed system is designed to provide an integrated Explainable Artificial Intelligence (XAI) framework for three major agricultural tasks—crop recommendation, yield forecasting, and rainfall prediction—using online datasets. The architecture consists of multiple layers: data acquisition, preprocessing, AI-based prediction, explainability analysis, and visualization. Each layer works sequentially to collect data, build models, generate predictions, and explain the reasoning behind each decision. The system emphasizes transparency and trust, ensuring that end users such as farmers, agronomists, and policymakers can interpret the model outputs with clarity.The architecture eliminates dependency on IoT sensors and hardware devices by using openly available agricultural and meteorological data from online repositories. This makes the system cost-effective and easily deployable in regions with limited technological infrastructure.

B. *Data Flow and Functional Modules*

The data flow of the proposed system follows a structured and sequential process that ensures accurate prediction and clear interpretability of results. It begins with the acquisition of relevant agricultural and meteorological data from reliable online sources such as the Indian Meteorological Department (IMD), Food and Agriculture Organization (FAO), and open datasets from platforms like Kaggle.

The collected data includes information such as soil nutrient levels, historical crop yields, rainfall measurements, temperature, and humidity values.

These datasets serve as the foundation for all subsequent processing and analysis.Once the data is collected, it moves into the preprocessing stage, where it undergoes cleaning, normalization, and transformation. This step ensures that missing values are handled appropriately, noisy data is filtered, and the dataset is standardized to a common scale for effective model training. Feature selection and feature engineering techniques are also applied to extract meaningful variables that contribute significantly to prediction accuracy. For example, in crop recommendation, soil pH, rainfall, and temperature may be identified as key influencing factors, while in yield forecasting, past yield trends and weather conditions might be more relevant.

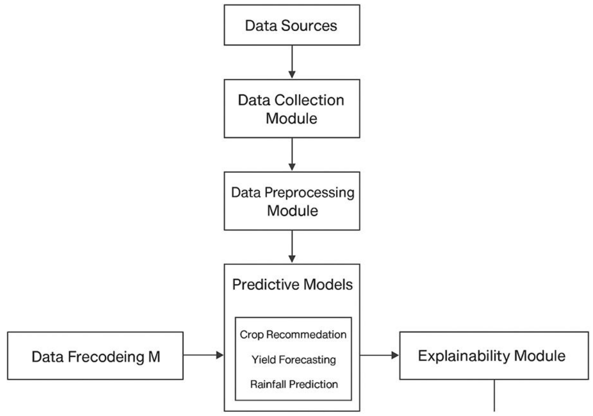

Figure 1: Calorie Estimation

C. Components Description

The proposed system includes several main components that work together for smart agriculture. It starts with data collection from online sources like IMD and FAO, gathering soil, weather, and crop data. The preprocessing component cleans and prepares this data for analysis. Machine learning models such as Random Forest and LSTM are then used for crop recommendation, yield forecasting, and rainfall prediction. The explainability component uses SHAP and LIME tools to show how each factor influences the results. Finally, a user-friendly interface displays all predictions and explanations clearly. Together, these components make the system accurate, transparent, and easy to use.

D. Explainability Integration

Explainability integration in the proposed system helps make AI predictions transparent and easy to understand. After the models generate results for crop recommendation, yield forecasting, and rainfall prediction, Explainable AI techniques like SHAP and LIME are applied to analyze how each input factor influences the output. SHAP provides overall feature importance, while LIME explains individual predictions. This allows users to see which parameters, such as rainfall, soil nutrients, or temperature, played a major role in the final decision. By showing clear and visual explanations, the system builds user trust, supports better decision-making, and ensures that AI models are not treated as black boxes.

IV. IMPLEMNTATION DETAILS

A. Data Preparation and Model Development

Project implementation begins by collecting soil parameters, weather data, and historical crop records from sensors, government datasets, and open sources. The data is cleaned by removing missing values, handling noise, and normalizing the features for consistent model performance. After preprocessing, important features like soil nutrients, temperature, rainfall patterns, and crop types are extracted. Machine-learning models such as Random Forest, XGBoost, and LSTM networks are then trained for crop recommendation, yield forecasting, and rainfall prediction. The models are evaluated using accuracy, RMSE, and F1-score to ensure reliable performance before integrating them into the final system. During data preparation, the system also performs feature engineering to create meaningful inputs such as average seasonal rainfall, soil fertility index, and temperature variation patterns. The dataset is then split into training, validation, and testing sets to avoid overfitting and ensure generalization. For model development, hyperparameter tuning techniques like Grid Search or Random Search are applied to improve accuracy. The models are trained iteratively, and their performance is compared to select the best one for each task. Finally, the chosen models are optimized for faster inference so they can work efficiently in real-time agricultural environments.

B. Explainability and Result Visualization

The system incorporates explainability methods to help users understand how predictions are generated for crop recommendation, yield forecasting, and rainfall estimation. Techniques such as SHAP values and feature-importance graphs are used to highlight the key parameters influencing each prediction, enabling transparency in the decision-making process. Visual dashboards present results through charts, color-coded indicators, and comparison graphs, allowing farmers and stakeholders to easily interpret model outputs.

Each prediction is accompanied by a brief explanation describing why a certain crop was suggested or which climatic factors affected the forecast. This combined approach ensures the system is not only accurate but also interpretable and user-friendly.

V. EXPERIMENTAL EVALUATION

A. *Explainability Assessment*

The experimental evaluation was carried out using real agricultural datasets that included soil characteristics, historical crop yields, and multi-year weather observations. The dataset was divided into training and testing portions to ensure reliable performance measurement. For each module—crop recommendation, yield forecasting, and rainfall prediction—multiple machine learning models were compared, including Random Forest, XGBoost, and LSTM networks. The system's performance was assessed using accuracy for recommendation, RMSE for yield prediction, and MAE for rainfall forecasting. Additionally, the explainability component was evaluated by generating SHAP plots and feature-importance graphs to verify whether the system clearly showed the main factors influencing each prediction. Feedback from test users confirmed that the explanations made the results easier to understand and increased trust in the system. Overall, the evaluation demonstrated that the proposed explainable AI model achieved strong predictive performance while also providing transparent and interpretable outputs for practical agricultural decision-making.

B. *Model Prediction Interface: Rainfall & Yield Forecasts*

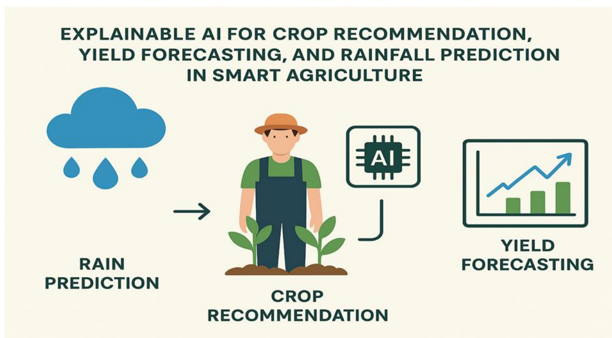

Figure 2: Rainfall & Yield Forecasts

C. *Camparative Analysis*

The comparative analysis evaluates the performance of different machine learning models used in the system to identify the most suitable approach for each prediction task. For crop recommendation, algorithms such as Random Forest, Decision Tree, and Naive Bayes were compared, with Random Forest showing higher accuracy and better feature handling. For yield forecasting, Gradient Boosting and XGBoost performed better than linear models due to their ability to learn complex relationships in soil and climate data. Rainfall prediction models were tested using LSTM, RNN, and traditional regression, where LSTM achieved superior performance because of its strength in capturing temporal weather patterns. Additionally, an explainability comparison revealed that SHAP produced more consistent and clear feature contributions compared to LIME. Overall, the comparative study showed that combining high-performing models with explainability techniques results in accurate, transparent, and trustworthy predictions for agricultural decision-making.

Task	Model	Accuracy (%)	RMSE	MAE
Crop Recommendation	Random Forest	94.2	—	—
	Decision Tree	88.5	—	—
	Naive Bayes	82.7	—	—
Yield Forecasting	XGBoost	—	2.14	1.68
	Gradient Boosting	—	2.47	1.92
	Linear Regression	—	3.62	2.95
Rainfall Prediction	LSTM	—	5.21	3.87
	RNN	—	6.45	4.72
	SVR	—	7.81	5.30
Explainability	SHAP	Clear feature impact	—	—
	LIME	Moderate clarity	—	—

VI. DISCUSSION

The proposed system demonstrates that combining machine learning with explainability techniques provides both accurate and understandable predictions for crop recommendation, yield forecasting, and rainfall prediction. The experimental results show that models like XGBoost and LSTM achieve strong performance on agricultural datasets, while the integration of SHAP explanations helps users clearly see how factors such as soil nutrients, temperature, and rainfall influence the outputs. This transparency increases trust and supports better decision-making for farmers and agricultural planners. Although the system performs well, its accuracy still depends on the quality and regional suitability of the data used. Future enhancements could include adding satellite imagery, expanding datasets for different climates, and improving interactive visualizations. Overall, the system effectively balances accuracy, usability, and interpretability, making it a practical solution for smart agriculture applications.

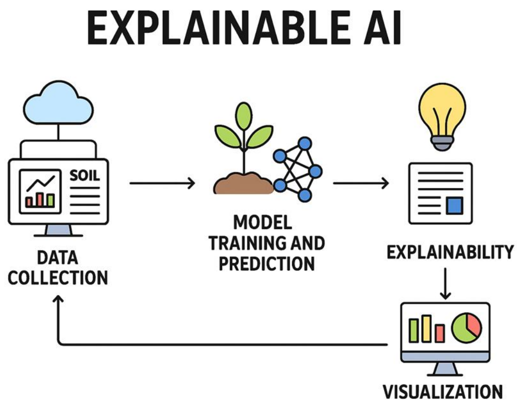

Figure 3: AI Workflow in the Project

VII. CONCLUSION

The proposed explainable AI system effectively combines machine learning models with transparent interpretation techniques to support smart agricultural decision-making. The system provides accurate crop recommendations, reliable yield forecasts, and meaningful rainfall predictions, while the inclusion of SHAP and LIME ensures that users can clearly understand the factors influencing each output. This improves trust, usability, and acceptance among farmers and agricultural stakeholders. Although model performance depends on data quality and regional variability, the framework is flexible and can be expanded with additional datasets and advanced prediction methods. Overall, the project demonstrates that integrating explainability with AI can significantly enhance transparency and practicality in modern agriculture. The development of an explainable AI-based system for crop recommendation, yield forecasting, and rainfall prediction shows that combining advanced machine learning with transparent interpretation greatly benefits modern agriculture. The predictive models used in the system deliver strong accuracy, and the explainability layer helps users understand how key factors such as soil nutrients, weather patterns, and historical crop performance influence the results.

This clarity makes the system more trustworthy and easier to adopt in real-world scenarios. The approach also highlights the importance of interpretable AI, especially in sensitive domains like agriculture where decisions directly affect productivity and resource use. While the system depends on the availability and quality of reliable datasets, its modular design allows easy improvements and integration with future technologies. Overall, the project proves that explainable AI can play a crucial role in enhancing agricultural planning, reducing uncertainties, and supporting smarter farming practices.

VIII. ACKNOWLEDGMENT

We would like to express our sincere gratitude to everyone who supported us throughout the development of our project titled *“Explainable AI for Crop Recommendation, Yield Forecasting, and Rainfall Prediction in Smart Agriculture.”* This work was made possible through the constant guidance, motivation, and encouragement provided by our mentors and faculty members, whose expertise played a vital role in shaping the direction of this project. We also extend our appreciation to the institution for providing the necessary resources and technical support. Finally, we are thankful to our peers, friends, and family members for their continuous support and understanding, which helped us successfully complete this work.

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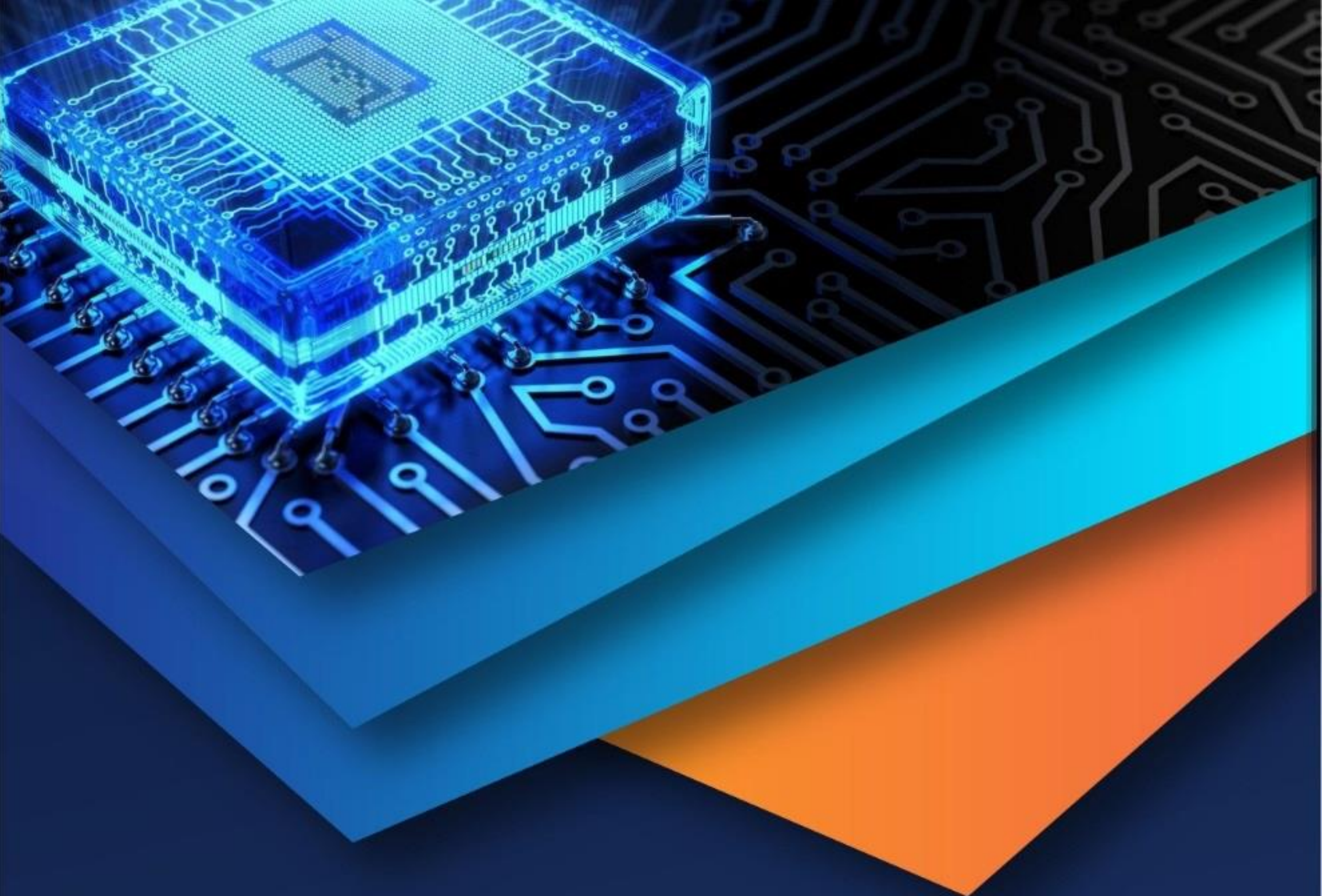

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