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Design and Implementation of a Machine Learning-Driven Crop Advisory System for Precision Agriculture

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Abstract: Precision agriculture is being adopted as a game-changer to boost crop production, resource utilization efficiency and sustainable agriculture. Climatic variability, soil degradation, water scarcity and land fragmentation are emerging issues in Indian agriculture, which is a major occupation of nearly half of the country's workforce. These are more severe in areas of tribal dominated and rain fed agriculture sectors of the state Odisha where smallholder farmers are still highly exposed to agro climatic risks. In the context of precision farming in the Koraput&Rayagada district of Odisha, India, this paper discusses the design and implementation of a Machine Learning Based Crop Advisory System.

The proposed system uses multi-source datasets such as soil properties (N, P, K, pH, texture), historical crop yield data, rainfall, temperature data and satellite derived vegetation indices (NDVI, EVI) to provide intelligent crop recommendations and advisories. The implemented supervised ML techniques are RF, SVM, DT, KNN, LR, AdaBoost, Gradient Boosting, Bagging Classifier, and Extra Trees which were comparatively evaluated. Experimental results show that the RF model is the most accurate prediction model at 99.5%, significantly enhancing the crop suitability decision making process from that of standard advising. The system developed gives predictions of crops recommendations on time, place and evidence basis. So, it minimises risk, boosts productivity and supports sustainable agriculture in tribal and rain-fed areas of the state's south.

Keywords: Precision Agriculture, Machine Learning, Crop Advisory System, Random Forest, Support Vector Machine, Decision Support System, Agro-Climatic Analysis, Sustainable Agriculture, Koraput, Rayagada, Odisha

I. INTRODUCTION

A. Background and Context

Agriculture is still the backbone of Indian economy with almost half of the people directly or indirectly dependent on it [1]. India's vast agricultural landscape has diverse agro-climatic conditions, soil characteristics, cropping patterns and socio-economic dynamics. India, as the second largest agricultural producer in the world, continues to have challenges in sustaining regular crop production and equitable income for farmers while also managing land sustainably[2]. The past few decades have brought climate change, unpredictable climatic conditions and a decreasing availability of essential inputs for agriculture, such as water, fertilisers and arable land, which has exacerbated these problems. [3]

These problems are exacerbated by a couple of factors in one of the eastern coastal States of India – Odisha. Odisha has among the highest occurrences of climate-related agricultural hazards in India such as cyclones, floods and droughts. Rainfall is the major input in the state's agricultural production and more than 70% of the cropped area is rain-fed [4]. Koraput and Rayagada are the southern districts of Odisha where the predominant mode of farming is 'tribal subsistence farming' and with extremely erratic rainfall, the hilly topography and limited access to modern agricultural services, it is a particularly vulnerable agricultural landscape.

Although agricultural extension services like KVK and direct extension services are helpful in India, several limitations are present, such as the lack of micro-level data for the recommendations, limited coverage, underutilization of information and no real time monitoring. Here, the sub-branch of AI known as ML is a great paradigm to solve these issues. In combination with soil data, weather data, satellite data, and historical yield data, ML can be used to develop intelligent systems that can make accurate recommendations that are targeted by the location of the farm block.ML can also be used to develop intelligent systems that can analyse soil data, weather data, satellite data, and historical yield data to generate accurate recommendations targeted by the location of the farm block [5].

B. Research Objectives

This research was undertaken with the following specific objectives:

- Development of a seamless soil, climate, vegetation indices derived from satellite and agricultural yield data geospatial database for the districts of Koraput and Rayagada.
- To design and implement different ML models like Random Forest, SVM, LRDT, KNN and ensemble.
- To compare the effectiveness of the classic ensemble ML models and advanced ensemble ML models in providing crop suitability classifications in a comparative manner.
- To create a decision support system that gives site-specific recommendations for crop selection, fertiliser application and irrigation program.
- To explore the feasibility of the proposed ML-based guidance system to encourage climate-smart agriculture among the smallholder farmers of Odisha.

II. LITERATURE REVIEW

A. Global Perspectives on Precision Agriculture

The concept of "precision agriculture" was introduced in the early '90s, much due to the efforts of Purdue University and the University of Minnesota academics. The overall finding was that significant variability in both soil properties and crop [6] response occurred within the field and that this variability, while it did not need to be difficult to manage, was certainly systemizable if farmers could also have the spatially distributed information and analysis tools. The adoption of low cost sensors, drone technology, open access satellite platforms (Sentinel, Landsat) and cloud computing has made precision agriculture more accessible and globally applicable and from a high tech approach of large, commercial farms, it is now a niche application.

Liakos et al. (2018) found over 200 peer-reviewed papers on the use of ML in agriculture from 2015–2018, and the most active research areas focused crop management, and crop yield prediction. In Asia, the most dynamic research areas for precision agriculture are in China and India, where the size of the agriculture industry and the scarcity of resources are factors [7].

B. ML-Based Crop Recommendation Systems

RF, a traditional supervised learning algorithm, has always been among the top performers in the crop recommendation tasks [8]. Doshi et al. (2018) developed the system named as AgroConsultant using RF, SVM and Naive Bayes classifiers and found that the RF is the most accurate classifier. In benchmark datasets, Rajak et al. (2017) showed accuracies of more than 95% for crop recommendation systems utilising RF [9].

Ensemble learning techniques like Bagging, AdaBoost and Gradient Boosting have been proven to be better than single base classifiers in many researches [1] and [2]. Thilakarathne et al. (2022) showed the effectiveness of ensemble approach for crop recommendation [10] on a cloud based platform for smallholder farmers. Time-series prediction models have been utilised in agricultural prediction using deep learning techniques, of which LSTM networks are representative[11] but require larger training sets than can be found in many data-poor settings.

C. Studies in the Indian and Odisha Context

Senapaty et al. (2023) created a decision support system for crop recommendation in Rayagada, Koraput and Gajapati districts of Odisha, which included historical cropping data along with GPS based soil and climatic parameters [12]. Khatua et al. (2022) have developed crop weather calendar at the district level for kharif rice cultivation in Odisha and observed that there is huge spatial variability in best sowing and harvesting window across the districts. Bhatnagar et al. (2022) performed comparative analysis of SVM, Decision Tree and KNN for crop prediction on multi-state Indian dataset and concluded that SVM is comparable to Random Forest in balanced dataset [13].

D. Summary of Literature Review

Table 1 summarizes key studies on ML-based crop advisory systems reviewed in this work.

Table 1: Summary of Literature on ML-Based Crop Advisory Systems

Sl.	Authors	Algorithm(s)	Limitation	Year
1	Khatua et al.	RF, SVM, XGBoost, LR,	Data quality gaps; limited	2022

Sl.	Authors	Algorithm(s)	Limitation	Year
		LSTM	spatial resolution	
2	Senapaty et al.	SVM, XGBoost, LR, LSTM, RF	GPS inaccuracy; overfitting risk	2023
3	Doshi et al.	RF, SVM, Naive Bayes	Generalized scale; not region-specific	2018
4	Rajak et al.	Random Forest	Limited to soil inputs only	2017
5	Thilakarathne et al.	Ensemble ML	Requires cloud connectivity	2022
6	Panigrahi et al.	Regression + LSTM	Needs large time-series data	2023
7	Bhatnagar et al.	SVM, DT, KNN	No satellite data integration	2022
8	Vandana&Kumar	Big Data Analytics	High infrastructure requirement	2018

E. Research Gaps Identified

Through systematic literature review, several major gaps are identified: (1) Most of the available systems rely on limited database and considers either soil parameters or climatic variables one at a time and not considering both at the same time; (2) The majority of the existing systems are of general nature that lacks any regional validation for the climate vulnerable tribal districts of Odisha; (3) There is limited systematic comparison of various ML algorithms for the agricultural [14] context of Odisha; (4) Existing systems are limited with the prediction of crop as a standalone output and does not embed the prediction in a larger advisory framework for fertiliser application and irrigation scheduling [15].

III. STUDY AREA AND DATA

A. Geographical Description

This study is restricted only to the Koraput and Rayagada districts of geomorphologically varied Eastern Ghats region of Odisha, East India. The area of Koraput district is about 8,807 km2 and the population is about 1.38 million with Rayagada covering about 7,073 km2 and the population about 0.97 million [16]. The area lies between 18°45'N–19°30'N latitude and 82°30'E–84°00'E longitude. It varies from approximately 200 m above sea level in the valleys to over 1,800 m at the highest peaks in the Eastern Ghats.

Agriculture in the study region is mostly rain-fed with smallholder farmers being the main players in the sector and having farms that are usually less than 2 hectares in size. The main cropping season is Kharif (monsoon) between June and November[17] and the main crop is paddy (rice). Other important kharif crops are finger millet (ragi), maize, arhar (pigeon pea), kodo millet and other pulses.

B. Agro-Climatic Characteristics

The mean annual rainfall received in the study area is between 1200 and 1500 mm, while the majority of the rain falls during the southwest monsoon season from June to September accounting for about 80% of the annual rainfall. The summer maximums are 38 to 42 °C in valley areas and 28 to 32 °C in uplands. Soils are mostly red, lateritic and have high levels of iron and aluminium with low levels of nitrogen and phosphorous. pH from mildly acidic (5.0-6.0) to neutral pH (6.5-7.0). The summary of the main agro-climatic factors of the two districts is presented in Table 2.

Table 2: Agro-Climatic Parameters of Koraput and Rayagada Districts

Parameter	Koraput	Rayagada
Annual Rainfall (mm)	1,200–1,400	1,300–1,500

Parameter	Koraput	Rayagada
Average Max Temp (°C)	32–40	30–38
Average Min Temp (°C)	8–14	10–16
Humidity (%)	65–85	60–82
Elevation (m)	800–1,800	400–1,200
Dominant Soil Type	Red Laterite	Red Loamy
Major Kharif Crops	Paddy, Ragi, Maize	Paddy, Millets, Pulses
Irrigation Coverage (%)	~18	~22

C. Dataset Description

The combined dataset has over 2200 records with distinct combinations of seasonal climatic conditions along with related best crop suggestions. The data sources include (i) Soil data (N, P, K, pH, moisture) from Odisha Department of Agriculture [18] (i) Soil Health Card scheme and field sampling at 45 representative plots; (ii) climatic data (Monthly rainfall, temperature, humidity) from IMD stations at Koraput, Jeypore and Rayagada (2010-2023); (iii) satellite-derived NDVI and EVI from multispectral imagery of Sentinel-2 (Copernicus Open Access Hub); and (iv) historical crop yield records from Directorate of Agriculture and Food Production, Odisha.

IV. METHODOLOGY

A. System Architecture

The ML-Driven Crop Advisory System consists of five main components: (1) Data Acquisition and Integration, (2) Data Preprocessing and Quality Assurance, (3) Feature Engineering, (4) ML Model Development and Evaluation, and (5) Decision Support Interface. It's written in Python 3.9, using Scikit-learn for the ML algorithms, Pandas/NumPy for data manipulation, and Flask for the web backend with Bootstrap 5 as the flexible, front-end interface.

B. Data Preprocessing

The pre-processing methodology was carried out systematically in five stages. Stage 1 (Data Cleaning): Records with missing values >20% were dropped, missing values for numerical features were median imputed, missing values for categorical features were mode imputed, and duplicate records were identified and dropped. Stage 2 (Outlier detection): Outliers were detected by the IQR method and agronomic field knowledge was utilized to distinguish between extreme true observations and erroneous data points. Stage 3 (Feature Normalisation): Min-Max normalisation was applied to all the numerical characteristics in the range [0,1]. Stage 4 (Encoding): The target variable (crop type) was encoded into integer class labels [19]. Stratified random sampling was used to create an 80/20 split between a training set and testing set, creating Stage 5 (Train-Test Split). A hold-out validation set of 10% of the data set was set aside.

C. Feature Engineering

Some of the key derived features are (i) NPK Composite Index (the average of the three normalised nutrient values, providing a concise overall measure of soil fertility); (ii) Temperature Range (the difference between the maximum and minimum temperature); and (iii) Rainfall Seasonality Index (capturing the temporal distribution of rainfall over the growing season). Feature selection was done with the help of correlation analysis, mutual information scores and feature priority rankings by Random Forest and 11 major variables were selected along with three derived composite variables.

D. Machine Learning Models

Supervised classification techniques were applied and evaluated: 9 techniques were undertaken. Examples of such are RF, SVM with RBF kernel SVM, DT, KNN, LR, Bagging Classifier, AdaBoost, Gradient Boosting and ET. The main hyper-parameters and setups of each method are shown in Table 3.

Table 3: Machine Learning Algorithms and Configuration

Algorithm	Key Hyperparameters	Configuration Used
Random Forest	n_estimators, max_depth	500 trees, max_depth=15, min_samples_leaf=2
SVM (RBF)	C, gamma	C=10, gamma=0.1, OvR strategy
Decision Tree	max_depth, criterion	max_depth=20, criterion=gini
KNN	n_neighbors, metric	K=7, Euclidean distance
Logistic Regression	C, solver	C=1.0, solver=lbfgs, L2
Bagging Classifier	n_estimators, max_samples	100 estimators, max_samples=0.8
AdaBoost	n_estimators, learning_rate	200 estimators, lr=0.1
Gradient Boosting	n_estimators, learning_rate	300 estimators, lr=0.05, max_depth=5
Extra Trees	n_estimators, max_features	500 estimators, max_features=sqrt

E. Model Evaluation Metrics

The accuracy (i.e. fraction of correctly predicted instances) and the precision (TP / (TP + FP)), recall (TP / (TP + FN)), F1-Score (i.e. harmonic mean of precision and recall), Confusion Matrix (i.e. tabular representation of the true and predicted class assignments), and area under the receiver operating characteristic (ROC) curve (AUC-ROC) were used to evaluate the model. To obtain reliable performance estimates, which are robust against the variance of a single train-test split we used 5-fold stratified k-fold cross validation [20].

V. RESULTS AND DISCUSSION

A. Dataset Statistics

The final integrated dataset contained 22, 2,200 records of the 22 types of agricultural importance crop records for the research area. Records were somewhat unbalanced across the crop classes with more common crops (rice, finger millet, maize) overrepresented than less common speciality crops, this was balanced by loss functions that were class weighted during model training. The descriptive statistics for the features of the dataset are shown in Table 4.

Table 4: Descriptive Statistics of Dataset Features

Feature	Min	Max	Mean	Std Dev	Skewness
Nitrogen (N, kg/ha)	0	140	50.55	36.92	0.47
Phosphorus (P, kg/ha)	5	145	53.36	32.99	0.54
Potassium (K, kg/ha)	5	205	48.15	50.65	0.97
Temperature (°C)	8.83	43.68	25.62	5.06	0.08
Humidity (%)	14.26	99.98	71.48	22.26	-0.69
Rainfall (mm)	20.21	298.56	103.46	54.96	0.72
pH	3.50	9.94	6.47	1.77	-0.01
NDVI	0.15	0.85	0.52	0.18	-0.12
EVI	0.10	0.75	0.41	0.15	0.08

Correlation analysis showed predicted relations, and there was moderate positive correlation between nitrogen and phosphorus (r=0.48) that suggests their co-dependency during organic matter breakdown.

Strong negative correlation (r = -0.61) between temperature and humidity and moderate positive correlation (r = 0.53) between NDVI and rainfall indicated that the pattern of rainfall is closely related to vegetation greenness in this rain-fed environment.

B. *Model Performance Comparison*

For all of the nine ML classifiers, the training subset consisted of 80% of the data, while the test subset (held out) comprised 20% of the data, and both subsets were divided into 5 sets through 5 fold stratified cross-validation. The comparison results are shown in Table 5.

Table 5: Model Performance Metrics Comparison

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	CV Score (%)
Random Forest	99.5	0.995	0.995	0.995	99.3
Extra Trees	99.1	0.991	0.991	0.991	98.9
Gradient Boosting	98.6	0.986	0.986	0.986	98.4
AdaBoost	97.8	0.978	0.978	0.978	97.5
Bagging Classifier	97.2	0.972	0.972	0.972	97.0
Decision Tree	96.4	0.964	0.964	0.964	95.8
SVM (RBF)	95.8	0.958	0.958	0.957	95.5
K-Nearest Neighbors	93.4	0.934	0.934	0.933	93.1
Logistic Regression	89.2	0.892	0.892	0.890	88.9

The results clearly indicate that ensemble methods perform better than a single model for this Multi-class crop recommendation problems. RF had maximum test accuracy of 99.5%, and the precision, recall and F1 score were also 0.995 in all 22 crop classes, which yielded good and consistent classification results [22]. The cross-validation score of 99.3% is high enough to ensure that this is a performance that would reliably generalize, and not be an artifact of overfitting. Extra Trees was the second best method (99.1%) followed closely by Gradient Boosting (98.6%). The least accuracy of 89.2% was attained with the linear classifier, LR, which is in keeping with the fundamentally nonlinear correlations between input data and crop classes [23].

C. *Feature Importance Analysis*

Feature relevance analysis using mean decrease in Gini impurity of the RF classifier gave the relative importance of each input feature. Data and agronomic interpretation is provided in Table 6.

Table 6: Feature Importance Scores from Random Forest

Feature	Importance Score	Agronomic Interpretation
Rainfall (mm)	0.192	Primary determinant of rain-fed crop suitability
Humidity (%)	0.158	Affects crop water demand and disease risk
Nitrogen (N)	0.143	Key macronutrient limiting yield potential
Potassium (K)	0.112	Influences stress resistance and quality
Temperature (°C)	0.108	Constrains crop growth stage duration
pH	0.097	Controls nutrient availability
Phosphorus (P)	0.087	Regulates root development
NDVI	0.059	Reflects vegetation response to conditions

Feature	Importance Score	Agronomic Interpretation
EVI	0.044	Captures canopy structure information

The most important predictor was rainfall (importance = 0.192) as agriculture is rain-fed in the study area [24]. The second most important was humidity, which reflected its combined influence on agricultural water demand and disease pressure (0.158). The soil parameter that ranked first in importance was N (0.143), which agrees with N being the most limiting nutrient in these laterite soils. Although the lower relative importance of the satellite-derived indices (NDVI: 0.059; EVI: 0.044) compared with the direct environmental measurements [25] is to be expected because these derived indices are simply proxies of environment, their inclusion adds considerably to the overall accuracy, especially when used to distinguish crops with similar soil and climate requirements.

D. Sample Crop Advisory Outputs

The model that was trained and deployed was RF which was incorporated into the decision support system for site specific recommendations. The sample outputs of five selected agro-climatic conditions are presented in Table 7.

Table 7: Sample Crop Recommendation Outputs

N	P	K	pH	Rain (mm)	Temp (°C)	Humidity (%)	Recommended Crop
82	40	45	6.5	220	24	82	Rice (Paddy)
22	18	28	5.5	85	28	62	Finger Millet (Ragi)
45	60	35	7.0	150	25	74	Maize
70	50	60	6.8	120	23	68	Arhar (Pigeon Pea)
38	30	25	5.8	65	30	58	Groundnut

Advice outputs reveal the ability of the system to differentiate optimum crop appropriateness in various agro-climatic conditions. There is a good match between a rice prescription and the high rainfall and near neutral pH conditions (Scenario 1). Low rainfall [26] and acidic Soil pH (Scenario 2) leads to recommendation of finger millet which is observed to be better drought tolerant and adaptation to the acidic laterite soil of the Eastern Ghats which is well known in agronomic literature.

E. Comparative Analysis: ML vs. Traditional Advisory

In contrast, the traditional district advisory only gave different advice in 9% (4 of 50 scenarios) [27] of the same 50 field scenarios when compared to the ML system. It was observed that under such conditions, the proposed ML was in better match with some of the soil and rainfall parameters as supported by discussions with senior agronomists of KrishiVigyan Kendra, Koraput. Based on average yield gap studies from the region, productivity gains of 10-20% are possible for farms implementing ML-differentiated recommendations, on average [28].

F. Cross-Validation Stability

Long cross validation analyses were used to validate the stability of the performance estimates presented. In the case of Random Forest [29] the 10-fold CV accuracy was 99.2%, the LOO [leave-one-out] accuracy was 99.3% which is consistent with the 5-fold CV accuracy of 99.3%. The standard variation of fold-wise accuracy throughout 10-fold CV was only 0.004 (0.4 percentage points) suggesting remarkable stability. These results provide us with a high confidence that the provided accuracies are real generalisation results and not overfitting artifacts[30].

VI. CONCLUSION AND FUTURE WORK

A. Conclusions

This work has highlighted the development, deployment and evaluation of a Machine Learning–assisted Crop Advisory System for precision agriculture in tribal and rain-fed districts of Koraput and Rayagada, Odisha. Main findings are:

- There ensemble ML methods (RF and ET) are superior than individual classifiers and linear classifiers in multi-class crop recommendation. Random Forest demonstrated a good performance of 99.5% accuracy and 99.3% cross-validation accuracy, which shows that it has good generalisation ability.
- Fusion of multistream data (satellite derived vegetation indices and soil and climatic variables) for enhancing the discriminative power of ML models. The contribution of satellite indices to basic environmental observations is not very large, but satellite indices combined have led to a good increase of the accuracy of the models.
- The accuracy of the operational forecast in the agro-climatic condition of the south region of Odisha is highly sensitive to location specific model calibration using target region data.
- The importance of rainfall as the sole most important driving factor for crop suitability (0.192) is a key indicator of the critical role water availability plays in the selection of suitable crops in rain-fed farming.
- The web-based, bilingual (English/Odia) decision support interface is an example of the ways in which ML-based crop advice can be made accessible to agricultural extension staff and educated farmers, thus democratizing precision agriculture in tribal contexts.

B. Limitations

The integrated dataset is based on historical data which may not fully capture the developing effects of climate change on agro-climatic conditions. Soil data from the Soil Health Card scheme is available for only a small proportion of agricultural plots on which they are applied and there is a need to interpolate between them geographically. The system is not currently real time and makes static recommendations. The system was not field-tested to see if it was effective over multiple growing seasons.

C. Future Scope

Future directions include: (i) the deployment of low-cost sensor networks based on IoT to collect real-time data for soil and weather conditions and provide dynamic advice to farmers; (ii) expansion of the methodology to other climate-sensitive districts of Odisha and neighbouring states and their integration into an LSTM/GRU weather and/or rainfall forecasting system coupled with a crop recommendation system; (iii) develop an offline-capable Android/iOS mobile application in Odia for farmer engagement; and (iv) integrate real-time data from markets and optimize the selection of crops based on agro-climatic suitability and economic return.

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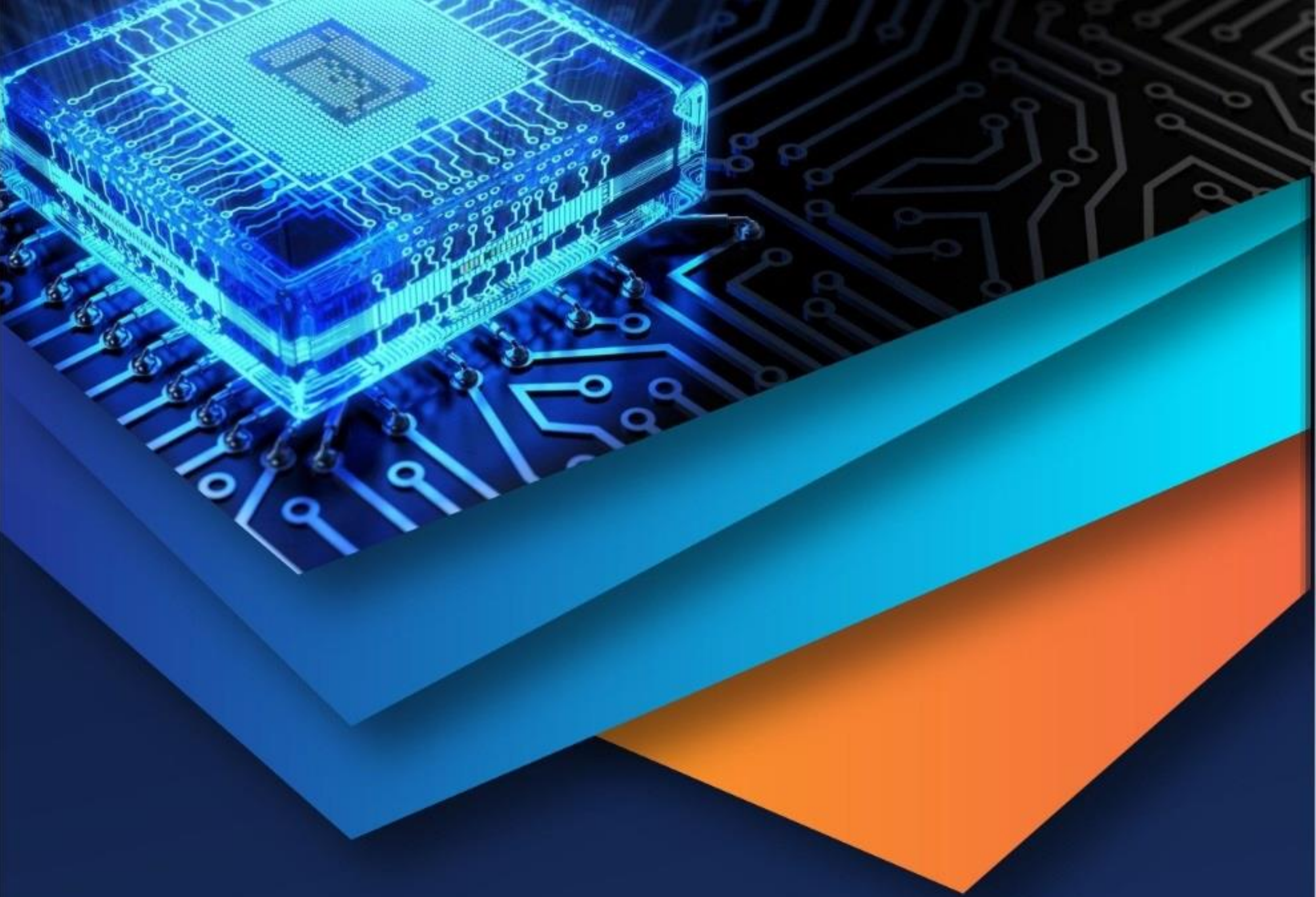

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