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Intelligent Crop Recommendation System Using Machine Learning

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Abstract: The intelligent crop recommendation system is aimed at helping farmers to pick the most appropriate crops, depending on the different environmental factors including the nutrients of the soil (NPK) as well as pH, temperature, humidity and rainfall levels. The system, through machine learning algorithms, such as random forest, support vector machine (SVM) and K-nearest neighbors (KNN), can estimate the best crops to be planted in various environmental conditions. Training is done with a large agricultural dataset which represents the key attributes needed to be classified when giving recommendations on crops. It is connected to an easy-to-use web interface to make it accessible and easily usable by the farmers. This system is also beneficial to sustainable farming since it can offer some insights on the application of data-driven knowledge that increases crop yield. This project will add value to the agricultural efficiency and sustainability through the use of technology and agricultural expertise.

Keywords: Crop Recommendation, Machine Learning, Random Forest, Support Vector Machine, K-Nearest Neighbors, Soil Nutrients, Sustainable Agriculture.

I. INTRODUCTION

Agricultural industry is very important in nourishing the entire world population yet it also poses a significant challenge in the ever-changing climatic conditions, including climate change, soil erosion, and water shortage [9]. Conventional agricultural methods are usually based on subjectivity and do not have the capacity of maximizing the choice of crops in accordance with the prevailing environmental conditions [18]. Anintelligent crop recommendation system can transform the manner in which farmers handle crop farming. With the help of data-driven insights, such a system can help farmers make the most appropriate choices regarding the types of crops that will be most suitable in their environment and, in the end, improve productivity and sustainability [2].The recent research has proven the efficiency of advanced machine learning and deep learning methods to enhance crop recommendation systems [1]. The current project seeks to create an Intelligent Crop Recommendation System that will utilize machine learning algorithms, including random forest, SVM, and KNN, in predicting the optimal crops when it comes to major environmental factors such as soil nutrients, pH, temperature, humidity, and rainfall [10]. The system is user-friendly and it is developed to make farmers get the right recommendations that are easy to understand [4]. This system can revolutionize the agricultural practice by integrating modern technology and agricultural skills to increase efficiency and sustainability besides guaranteeing maximum crop yield.

II. LITERATURE SURVEY

Machine learning has been extensively used to estimate crop recommendation systems in order to enhance agricultural output. Shastri et al. [2] offered a crop suggestion model based on Gradient Boosting and exhibits a better efficiency than the conventional models. In the same way, Afzal et al. [14] have integrated the soil and climatic parameters in the ensemble learning method and emphasize the significance of the multi-feature analysis. To increase transparency and readability, Shams et al. [15] proposed an explainable artificial intelligence (XAI)-based crop recommendation system. The system proposed by Baishya and Dutta [4] is a TinyML-based system of real-time crop recommendation that should be used in resource-constrained environments, which is why it can be applied to the rural setting. In the recent past, studies have been done on incorporation of advanced technologies with machine learning. Kumar et al. [6] offered an ensemble model with high prediction accuracy developed based on AI, whereas Sharma and Verma [7] used machine learning and integrated it with IoT to give real-time crop advice. Hybrid machine learning models were proposed by Nguyen et al. [8], and they are better than single algorithms. Past studies [18] by Priyanka et al. and [17] by Sujatha et al. used data mining and machine learning to predict crops and this was the basis of the contemporary crop recommendation systems. The research has indicated that soil nutrients, temperature, and rainfall are among the key environmental parameters.

Regardless of these developments, the current systems have also been characterized by such challenges as high level of complexity of computation, poor scalability and non-ease of implementation. Hence, the system which would be efficient and accurate in terms of the balance between the performance and usability is required.

III. PROPOSED SYSTEM

The suggested system will create an intelligent crop recommendation model, which will help the farmers to choose the best crops depending on the environmental and soil conditions. Compared to conventional practices that are based on manual decision-making, the system employs machine learning algorithms in an attempt to give precise and evidence-based recommendations. The system takes into account various input measures on the part of soil nutrients like nitrogen (N), phosphorus (P), and potassium (K), as well as climatic measures like temperature, humidity, pH and rainfall. The machine learning models are used to process these parameters in order to predict the most suitable crop to grow. In order to enhance predictability and guarantee a robust working system, the proposed system incorporates three popular machine learning algorithms: Random Forest, SVM, and KNN. These algorithms have been chosen because they perform well in classification functions and also, they are effective in processing structured agricultural data effectively.

The general system workflow will involve the following steps:

Data Collection: The data in the system is Crop Recommendation dataset offered at Kaggle which involves different environmental and soil parameters and their corresponding crop labels. The dataset would comprise of 2200 samples, 7 input features and 22 crop classes, 100 samples in each class, meaning that the dataset is balanced. The dataset is tested with 5-fold Stratified Cross Validation on which the dataset is broken into five equal subsets. Each of the iterations consists of four subsets (around 1760 samples) to train and one subset (around 440 samples) to test. This methodology guarantees the use of all the data points so that it can predict a suitable crop.

Data Preprocessing: The data is pre-processed by running label encoding to encode the categorical labels of crops into numerical data. The Standard Scaler is used to scale the features of the input and make its features uniform to enhance the performance of the model.

Algorithms:

Random Forest:

Random Forest is an ensemble machine learning algorithm which is a combination of multiple decision trees to enhance predictive accuracy and decrease overfitting. The trees are trained on a random set of the features and the dataset. The last forecast is provided by majority of all trees. Random Forest in this project offers the best accuracy based on its capacity to deal with complicated relationships in environmental parameters.

$$\hat{y} = \text{mode}(h1(x), h2(x), \ldots, h\_n(x))$$

Where:

- $h_i(x)$= prediction of each tree
- Final output = majority vote

SVM:

SVM is a supervised learning algorithm that can be utilized for classification. It operates by locating an optimal hyperplane which separates the various classes at maximum margin. SVM is useful with high-dimensional data and it offers desirable generalization. In the project, SVM is applied in order to classify crops by environmental features.

$$W \cdot x + b = 0$$

Optimization:

$$\min \frac{1}{2} \| w \|^2$$

Where:

- w= weight vector

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- b= bias
- Goal = maximize margin

KNN:

KNN is a non-parametric algorithm that is easy to use and classifies the data according to the majority of its neighbors. It estimates the distance between the data points and picks the K closest points. KNN is used to predict the type of crop in this project on similarities between the environmental conditions.

d = √(Σ_{i=1} ^{n} (x_i–y_i) ^2)

Where:

- x_i, y_i= feature values
- d= distance

Model Training:It makes use of 5-fold Stratified Cross Validation to estimate the processed data. Random Forest, SVM, and KNN machine learning models are also trained and tested at every iteration.

Hyperparameters:

Table 1: Hyperparameters of Machine Learning Models

Hyperparameters of ML Models

Model	Hyperparameter	Value
Random Forest	n_estimators	50
Random Forest	Max Depth	5
Random Forest	Min Samples Split	14
Random Forest	Min Samples Leaf	10
SVM	Kernel	Linear
SVM	C	0.05
KNN	n_neighbors	13
KNN	Weights	Uniform

Table 1 shows the hyperparameters used with the machine learning models to train. These are the parameters that are well chosen based on the aims of optimizing the model and enhancing the accuracy of prediction. Random Forest model employs multiple decision trees which have controlled depth whereas SVM and KNN parameters are adjusted to provide improved generalization.

Implementation Environment:

Table 2: Details of Implementation Environment

Implementation Details

Category	Specification
Processor	Intel Pentium i3
RAM	2 GB
Storage	500 GB Hard Disk
Operating System	Windows 10
Programming Language	Python
Framework	Flask
Libraries	Scikit-learn, Pandas, NumPy
Frontend	HTML5, CSS3, JavaScript
IDE	VS Code, Web Browser

The proposed system is implemented by use of standard hardware and software settings. It is coded on Python with Flask framework with machine learning packages, including Scikit-learn, Pandas, and NumPy. The application has been developed and tested in a Windows 10 platform with minimum hardware requirements, which is applicable in the real-life implementation.

- Model Evaluation: Accuracy, precision, recall and F1-score are used for evaluating each classifier. From the experiment results, it is evident that Random Forest classifier achieves an accuracy of 98%, which means that it is the most effective classifier.
- Prediction System: The trained model predicts the most appropriate crop with the input values provided by the user which includes the nutrients of the soil and the environmental conditions.
- User Interface: It is coupled with an easy-to-use interface that will enable farmers to input the parameters with simplicity and get crop recommendations in simple and understandable format.

IV. ARCHITECTURE

The offered system is designed with a systematic structure in order to deliver precise crop suggestions on the basis of soil and environmental factors. It starts with the farmer using a web-based interface, in which he/she enters the input. This interface makes it easy and efficient to interact with the users.

The input data is then processed at the backend where preprocessing operations like label encoding and feature scaling is done to pre-process the data before being fed to machine learning models. It is based on such algorithms as Random Forest, SVM and KNN. Reliable performance of the models is done by considering 5-fold Stratified Cross Validation.

After the model has been trained, it is put into prediction. The system takes the input of the user in the trained model and produces the most appropriate crop suggestion. The end product is presented in the form of the web interface, and this allows the farmers to make informed and data-oriented decisions.

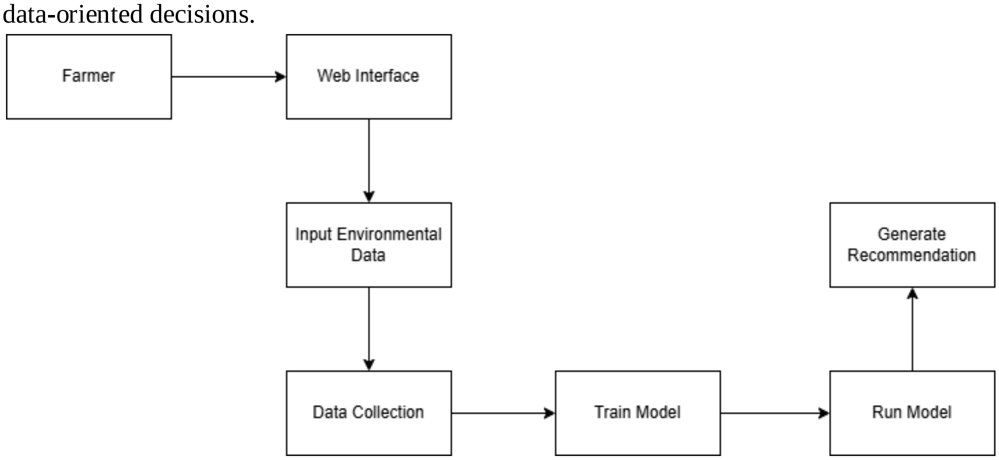

Fig.1:Proposed System Architecture

V. RESULT

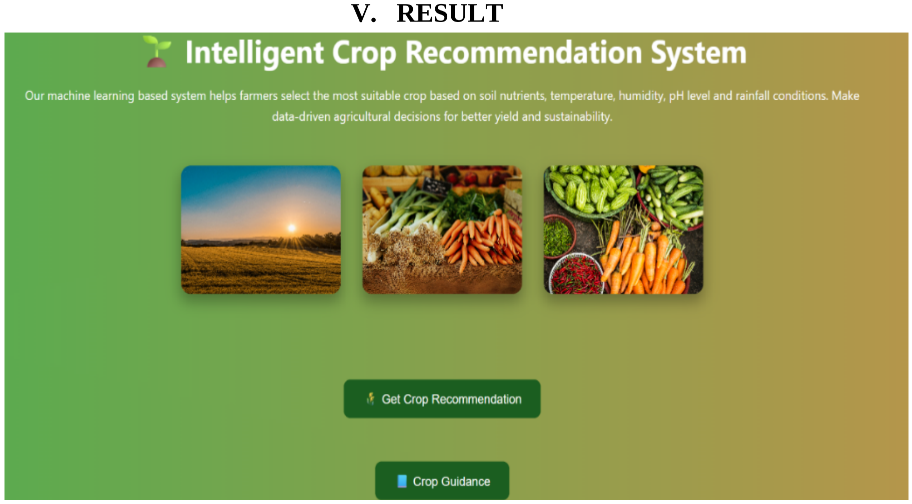

Fig.2: Home Page of Website

The system has a user-friendly web interface allowing a user to access crop recommendations with ease. It will show the object of the system and lead the users to key in soil and environmental parameters. The interface has such navigation choices as Get Crop Recommendation and Crop Guidance. In general, it guarantees easy and effective communication of farmers to make evidence-based decisions.

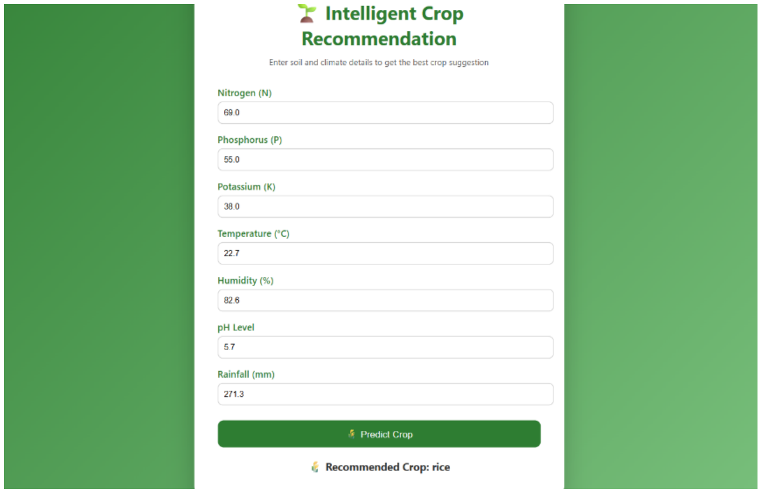

Fig.3: Output of the Execution

The suggested system will have a friendly interface enabling the use of the soil and environmental data. Depending on the values of the inputs, the machine learning model developed is used to predict the most appropriate crop. The trained Random Forest model is used to make this prediction and with the highest accuracy of 98% in the process of evaluation. The outcome shows that the specified environmental conditions are more or less similar to the optimum conditions of crop production. The graphical user interface also makes the system usable since any individual with limited technical capacity such as the farmers can easily interact with the system to retrieve results.

VI. MODEL EVALUATION

ACCURACY**:**Accuracy is an evaluation measure that measures the ability of the model to predict the correct crop from the input variables of the model. It computes the proportion of true positives and negatives to all predictions made by the system.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Having developed the proposed system, the accuracy of the system was 98.00 percent with the introduction of the Random Forest algorithm, and this shows that the proposed modelworks very well in forecasting the right crop in the specified environmental conditions.

VII. PERFORMANCE ANALYSIS

1) PRECISION:

Precision is the ratio of the number of correctly forecasted positives against the number of positives forecasted. It is the way well the model determines a particular crop.

Precision=TP/(TP+FP)

The accuracy of the proposed model is large in all the types of crops which means that the system can make correct predictions with very few false positives.

2) RECALL:

Recall is the proportion between correctly predicted positive observations to the total actual positive ones. It is used to measure the capacity of the model to be able to identify all the relevant instances.

Recall=TP/(TP+FN)

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The recall values are also very high as it is observed that the model successfully identifies most of the correct classes of crops without overlooking any important predictions.

3) F1-SCORE:

F1-score represents an equal measure of the harmonic mean of precision and recall, which gives a trade-off between the two measures.

$$F1=2\times(Precision\times Recall)/(Precision+Recall)$$

The F1-score of the model is near to 0.98 which shows the good balance between the precision and the recall and proves the power of the model.

4) MODEL COMPARISON:

The work of various machine learning solutions is assessed and contrasted to recognize the most efficient model to be applied in crop recommendation. Random Forest, SVM and KNN are evaluated with respect to the accuracy, precision, recall and F1-score. Random Forest is the most accurate of these models at 98 percent which is better because it has the capability of an ensemble learning model. Based on the comparison, it is apparent that the implications of Random Forest are more reliable and consistent than SVM and KNN.

```
===== RANDOM FOREST =====
Accuracy: 97.99999999999999
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	100
1	0.99	1.00	1.00	100
2	0.86	0.99	0.92	100
3	1.00	1.00	1.00	100
4	1.00	1.00	1.00	100
5	1.00	1.00	1.00	100
6	0.98	1.00	0.99	100
7	1.00	1.00	1.00	100
8	0.89	0.94	0.91	100
9	1.00	1.00	1.00	100
10	0.95	1.00	0.98	100
11	0.99	0.98	0.98	100
12	1.00	1.00	1.00	100
13	1.00	0.79	0.88	100
14	1.00	1.00	1.00	100
15	1.00	1.00	1.00	100
16	1.00	1.00	1.00	100
17	1.00	0.97	0.98	100
18	1.00	1.00	1.00	100
19	1.00	1.00	1.00	100
20	0.94	0.89	0.91	100
21	0.99	1.00	1.00	100
accuracy			0.98	2200
macro avg	0.98	0.98	0.98	2200
weighted avg	0.98	0.98	0.98	2200

Fig.4:Performance Analysis of Random Forest

```
===== SVM =====
Accuracy: 96.63636363636364
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	100
1	1.00	1.00	1.00	100
2	0.89	0.94	0.91	100
3	1.00	1.00	1.00	100
4	0.98	1.00	0.99	100
5	1.00	1.00	1.00	100
6	0.99	0.99	0.99	100
7	1.00	1.00	1.00	100
8	0.77	0.99	0.87	100
9	0.95	1.00	0.98	100
10	0.92	0.93	0.93	100
11	0.99	0.99	0.99	100
12	0.98	1.00	0.99	100
13	0.98	0.94	0.96	100
14	0.98	1.00	0.99	100
15	1.00	1.00	1.00	100
16	1.00	0.93	0.96	100
17	1.00	0.90	0.95	100
18	1.00	0.90	0.95	100
19	0.95	1.00	0.98	100
20	0.94	0.75	0.83	100
21	1.00	1.00	1.00	100
accuracy			0.97	2200
macro avg	0.97	0.97	0.97	2200
weighted avg	0.97	0.97	0.97	2200

Fig.5:Performance Analysis of SVM

```
===== KNN =====
Accuracy: 96.0
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       100
           1       1.00      1.00      1.00       100
           2       0.86      0.98      0.92       100
           3       1.00      1.00      1.00       100
           4       0.99      1.00      1.00       100
           5       1.00      0.99      0.99       100
           6       0.96      1.00      0.98       100
           7       1.00      1.00      1.00       100
           8       0.81      1.00      0.89       100
           9       0.94      1.00      0.97       100
          10       0.89      0.94      0.91       100
          11       1.00      0.96      0.98       100
          12       0.90      1.00      0.95       100
          13       0.99      0.85      0.91       100
          14       0.99      1.00      1.00       100
          15       1.00      1.00      1.00       100
          16       1.00      0.88      0.94       100
          17       1.00      0.96      0.98       100
          18       1.00      0.77      0.87       100
          19       0.90      1.00      0.95       100
          20       0.99      0.79      0.88       100
          21       1.00      1.00      1.00       100

    accuracy                           0.96      2200
   macro avg       0.96      0.96      0.96      2200
weighted avg       0.96      0.96      0.96      2200
```

Fig.6:Performance Analysis of KNN

Table 3: Comparison of ML Models

Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest	98.00	0.98	0.98	0.98
SVM	96.64	0.97	0.97	0.97
KNN	96.00	0.96	0.96	0.96

Comparison of the performance of the machine learning models applied in this study is shown in Table 3. The outcome indicates that the random Forest model has the best precision of 98 percent as compared to SVM and KNN. The values of precision, recall and F1-score also suggest that random forest makes more stable and reliable predictions.

VIII. CONCLUSION AND FUTURE SCOPE

This paper has come up with an Intelligent Crop Recommendation System that is founded on machine learning technologies in order to help farmers decide on the best crops depending on the soil and environmental conditions. The system has 7 important parameters that it uses in getting correct predictions. Random Forest was the best in accuracy with a score of 98 percent compared to SVM and KNN. The findings indicate that machine learning models can be appropriate to examine agricultural data and make valid crop recommendations. The suggested system will be easy to use and give farmers an opportunity to make decisions based on data, which will increase crop production and enhance sustainable agriculture. On the whole, the system is an effective and feasible answer to the present-dayagriculture. In the future, the system can be improved by adding real-time information in the form of the IoT sensors to give more dynamic and accurate recommendations. An app is possible to create, which will make accessibility easier to the farmers in distant places.

Moreover, weather forecasting and satellite information can also be added to enhance better prediction. It is also possible to expand the system to incorporate the recommendations of fertilizers and crop yield prediction. In addition, the system can be made more robust and scaled to the specific needs of various agricultural conditions using advanced deep learning models and datasets that are region-specific.

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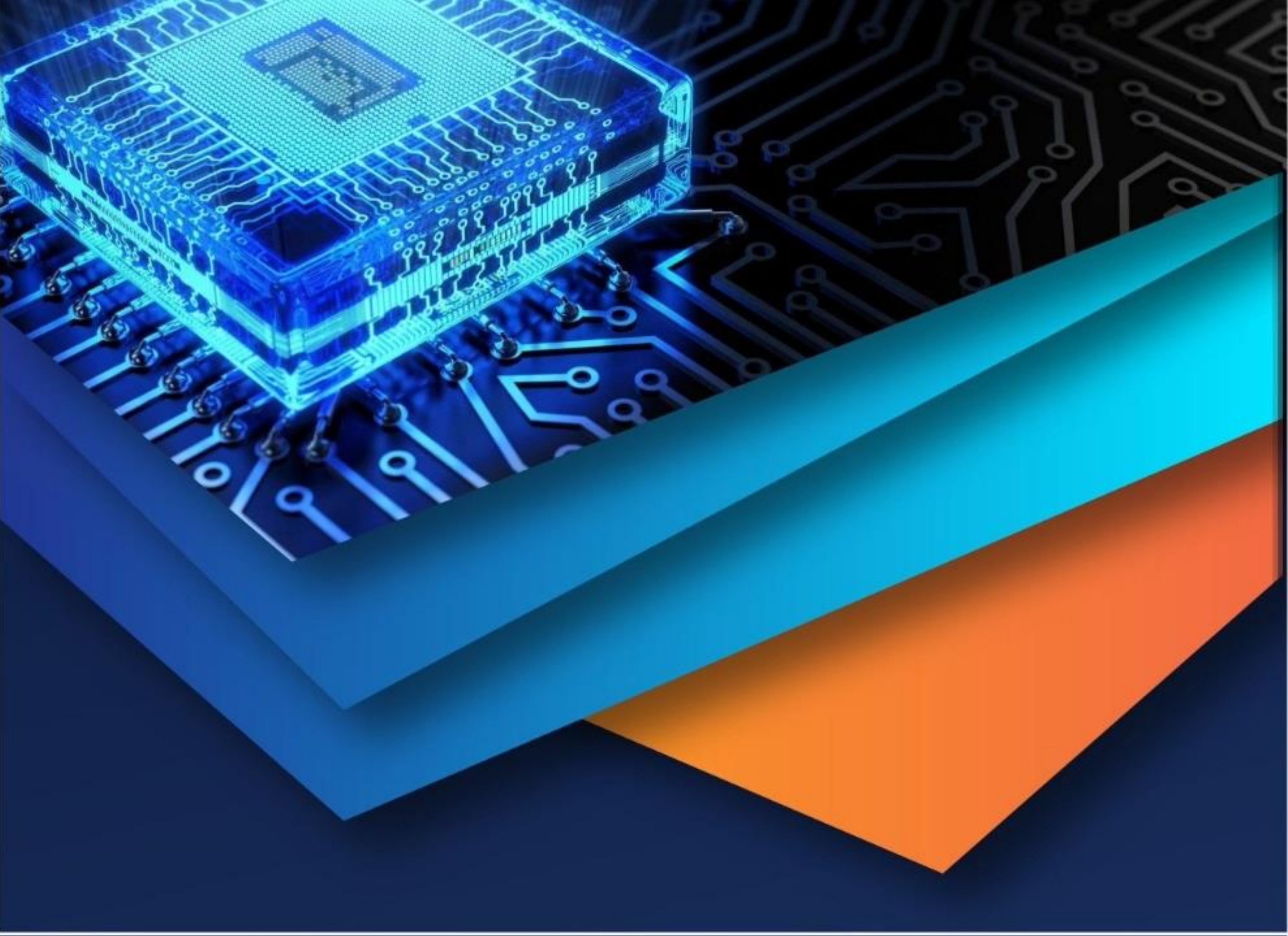

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