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A Deep Driven Smart Farming Systems for Sustainable Agriculture

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Abstract: Agricultural productivity is very sensitive to temporal variations in climate, heterogeneous soil conditions, and dynamic crop health. As such, precise crop yield forecasting constitutes a complex and multifactorial problem. Long-term temporal dependencies in agricultural datasets cannot be modeled by conventional statistical and machine learning approaches. An advanced deep learning-based framework for intelligent agricultural analytics presented this study integrates crop yield prediction with crop health assessment using multi-source datasets. Time series data that include meteorological parameters, soil characteristics, and historical yield records are modeled with Temporal Convolutional Networks (TCNs) to learn long-range seasonal dependencies effectively as well as temporal trends. For visual analysis of crops, both satellite imagery and leaf-level photographs go through a Vision Transformer (ViT) architecture wherein self-attention mechanisms are used to extract global spatial features so that subtle patterns related to the health of crops can be identified along with diseases affecting them. The framework uses publicly available datasets: the CY-Bench crop yield benchmark for predictive modeling; Indian historical crop yield and weather datasets for temporal analysis; and the PlantVillage image dataset for disease detection and visual feature extraction. Standard evaluation metrics such as accuracy, mean absolute error (MAE), and root mean square error (RMSE) will be used to assess performance. Results from experiments show that the proposed deep learning framework with TCNs plus Vision Transformers outperforms traditional models in capturing complex spatiotemporal patterns—hence improving accuracy plus reliability in both crop yield prediction as well as monitoring crop health.
Keywords: Smart Agriculture, Vision Transformer, Temporal Convolutional Networks, Crop Yield Prediction, Plant Disease Detection, Deep Learning, Precision Agriculture, Agricultural Analytics.

I. INTRODUCTION

Agriculture as an industry remains the bedrock of food security and economic stability across the globe, especially in developing countries whose larger population draws their livelihood from it. The productivity of the agriculture sector faces significant challenges due to factors such as climate change, heterogeneity of soils, pests, and plant diseases, as highlighted in recent studies on agricultural intelligence systems [1].

Weather conditions that change over time and the variability of soils and crops significantly influence crop yield outcomes, making accurate prediction a critical task in modern agriculture [3]. Thus, the need for precise crop yield prediction and effective crop health assessment has become an important research problem in smart sustainable agriculture [7].

In the agriculture domain, forecasting has largely relied on statistical models and traditional machine learning approaches such as regression and support vector machines [1]. While these models provide a foundational framework for prediction, they lack the capability to capture the complex nature of agricultural data. In particular, they fail to model long-term temporal dependencies of seasonal weather patterns [2] and are unable to effectively represent highdimensional spatial relationships present in visual crop data such as satellite or leaf images. These limitations make traditional approaches less suitable for realworld large-scale agricultural systems that require the integration of both temporal and spatial dynamics.

Recent advances in deep learning have introduced powerful solutions for handling such complex data. Temporal Convolutional Networks (TCNs), proposed for sequence modeling tasks, have demonstrated strong capability in learning long-term temporal dependencies in time-series data such as weather and crop yield information [3]. In parallel, the introduction of transformer architectures in computer vision, particularly the Vision Transformer (ViT), has enabled the modeling of global contextual relationships in images through self-attention mechanisms [2]. These models have been successfully applied in agricultural applications, including plant disease detection and crop analysis using leaf and satellite images, as demonstrated in several studies [7].

II. RELATED WORKS

A. *Traditional Approaches for Crop Yield Prediction*

Crop yield prediction has been treated using statistical and classical machine learning techniques such as linear regression, autoregressive integrated moving average (ARIMA), and support vector machines (SVMs), which are widely used to compute crop productivity based on historical agricultural data [13]. These methods primarily depend on structured inputs such as rainfall, temperature, and soil parameters. Although these approaches provide interpretable results, they are fundamentally limited in capturing non-linear relationships and complex interactions among multiple influencing factors. Additionally, their inability to model long-term temporal dependencies reduces their effectiveness in handling seasonal and climatic variability in agricultural data [14].

B. *Machine Learning–Based Agricultural Analytics*

To overcome some limitations of traditional models, machine learning techniques such as Random Forests, Gradient Boosting Machines, and Artificial Neural Networks (ANNs) have been applied for crop yield prediction and agricultural decision support [13]. These models improve predictive performance by capturing non-linear relationships between input features and yield outcomes. However, most conventional machine learning models treat temporal data as static features and fail to capture sequential dependencies inherent in time-series agricultural data. Furthermore, they require extensive feature engineering and domain expertise, which limits scalability and adaptability. Their performance also degrades when handling high-dimensional data such as satellite imagery and plant disease images.

C. *Deep Learning for Time-Series Modeling in Agriculture*

Recent advancements in deep learning have significantly improved the ability to capture temporal dynamics in agricultural datasets. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, are commonly used for modeling sequential data such as weather patterns and crop growth trends. However, these models suffer from issues such as vanishing gradients, high computational complexity, and limited parallelization. To address these challenges, Temporal Convolutional Networks (TCNs) have been proposed as an effective alternative for sequence modeling tasks [3]. TCNs utilize causal and dilated convolutions to efficiently capture longrange temporal dependencies while maintaining stable gradients, making them highly suitable for crop yield prediction using time-series agricultural data.

D. *Image-Based Crop Health Monitoring and Disease Detection*

In recent years, image processing techniques have gained significant attention for crop health monitoring and plant disease detection. Early approaches relied on handcrafted features such as color, texture, and shape descriptors, which were classified using methods like k-nearest neighbors (k-NN) and SVMs. With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for image-based agricultural applications. CNN architectures such as AlexNet, VGG, and ResNet have demonstrated high performance in plant disease classification using datasets like PlantVillage [1], [10]. However, CNNs primarily focus on local feature extraction through convolution operations and may not effectively capture global contextual relationships across the entire image [11].

E. *Vision Transformers for Agricultural Image Analysis*

Transformers, originally introduced for natural language processing, are increasingly being applied to computer vision tasks. The Vision Transformer (ViT) models images as sequences of patches and employs self-attention mechanisms to capture global relationships across the entire image [2]. In agriculture, Vision Transformers have been successfully applied to crop classification, disease detection, and satellite image analysis [4], [7]. Unlike CNNs, Vision Transformers can effectively model long-range spatial dependencies and global contextual information, making them highly suitable for complex agricultural imagery. Additionally, lightweight and hybrid transformer models such as MobilePlantViT further improve efficiency and scalability for realworld applications [9].

F. *Research Gap and Motivation*

Despite significant advancements in agricultural analytics, several research gaps remain. Traditional and machine learning approaches are insufficient for modeling complex spatiotemporal dependencies in agricultural data [13].

Although deep learning models have improved predictive performance, most existing methods treat temporal and spatial data separately, leading to suboptimal results. Furthermore, limited research has focused on integrating Temporal Convolutional Networks for time-series modeling with Vision Transformers for image-based analysis within a unified framework. This gap highlights the need for an integrated deep learning approach capable of simultaneously capturing long-term temporal dependencies and global spatial patterns. Therefore, this study proposes a unified framework that combines TCNs and Vision Transformers to enhance crop yield prediction and crop health analysis for intelligent and sustainable agricultural systems [8].

III. METHODOLOGY

A. System Overview

This paper proposes an intelligent smart farming framework that integrates time-series and image-based data for agricultural analysis. The system has two main tasks: predicting crop yield and assessing crop health. It uses a hybrid deep learning approach that combines Temporal Convolutional Networks (TCNs) to model temporal features and Vision Transformers (ViTs) to model spatial features. The overall workflow includes data acquisition, preprocessing, feature engineering, model training, evaluation, and visualization.

B. System Model

The system is designed as a multi-stage pipeline for heterogeneous agricultural data collected from various sources. The input data comprises time-series data such as weather parameters (temperature, rainfall, humidity), soil properties, and historical crop yield records, along with image data which contains plant leaf and satellite images.The collected datasets first go through a preprocessing stage where missing values are imputed, numerical features are normalized, and image data is resized and augmented. Feature engineering techniques are then applied to extract meaningful patterns from the dataset before splitting it into training and testing subsets.This processed data is fed into two parallel deep learning models: Temporal Convolutional Network (TCN): This model handles sequential data for crop yield prediction using dilated causal convolutions to capture long-term dependencies and seasonal variations in agricultural data. Vision Transformer (ViT): This model performs crop health analysis and disease detection by processing image data through patch division of images followed by self-attention mechanisms that help to extract global spatial features. Outputs from both models are then fused together for further refinement using hyperparameter optimization as well as feature selection techniques. The final output consists of predicted values for crop yields along with results related to classifications concerning the health of crops.

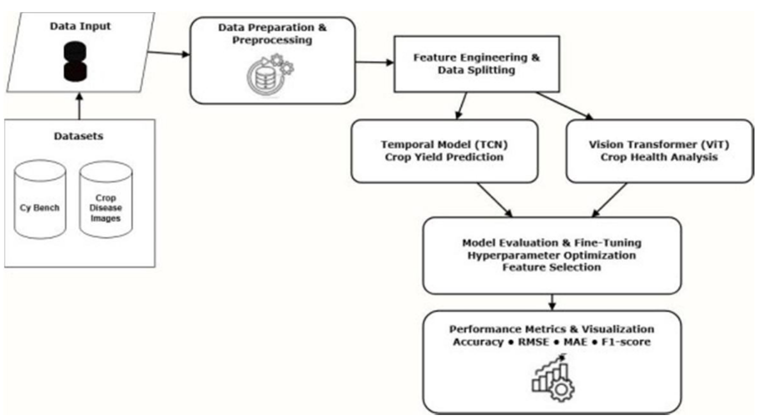

Fig: System Architecture

C. Mathematical Formulation

Let $X_t = \{x_1, x_2, \dots, x_n\}$be the time-series input data and $I = \{i_1, i_2, \dots, i_m\}$ be the image data. The system output is crop yield prediction Y and crop health classification C.

The temporal model is $Y = f_{TC}(X_t)$ where f_{TCN} is the Temporal Convolutional Network that maps sequential input data to yield predictions. The imagebased model is $C = f_{Vi}(I)$ where f_{ViT} is the Vision Transformer that extracts global spatial features from input images.

The final integrated output of the system is $O = (Y, C)$where O is a combined output consisting of yield prediction and crop health analysis.

D. Workflow Description

The general process of the system suggested is as follows: This includes datasets for crop yield and datasets with images of plant diseases. Next is the preprocessing of the data. Feature engineering and splitting of the data help in improving the performance of the models. Time-series data is processed through the TCN model for predicting crop yield. Image data is processed through the Vision Transformer for analyzing the health of the crops. The models are trained and tested using appropriate optimization techniques for fine-tuning them. Metrics for performance evaluation are in the form of values such as Accuracy, RMSE, MAE, and F1-score.

IV. DATASET AND PREPROCESSING

The datasets used to evaluate the proposed intelligent smart farming framework are the CY-Bench for crop yield prediction, Indian agricultural datasets for environmental parameters, and the PlantVillage dataset for crop disease detection. These datasets were chosen purposefully and not based on convenience sampling. Each one represents a different dimension of agricultural analysis: temporal variability in environmental conditions, soil and climatic diversity, and visual indicators of crop health.

Training on such heterogeneous data sources reduces dependence on any one data distribution and helps ensure that the model can generalize to different agricultural conditions. One major contribution of this work is to design a unified preprocessing pipeline that aligns structured time-series data with unstructured image data into a common feature space while maintaining important agricultural patterns.

A. Crop Yield and Environmental Dataset

The crop yield dataset (CY-Bench) serves as the primary data source for modeling temporal agricultural patterns. It comprises historical crop yield values and associated environmental features like temperature, rainfall, and humidity.The dataset captures seasonal variations and long-term dependencies that are essential for accurate yield prediction. However, there is a significant difference in the distribution of yield values across regions and crop types, which introduces natural variability into the data.Moreover, Indian agricultural datasets offer soil-related parameters including moisture levels and nutrient content. These datasets add to the yield data by introducing environmental diversity and allowing the model to learn about relationships between soil conditions and crop productivity.Yield and environmental datasets are combined to create a realistic setting where multiple interdependent factors influence the prediction task.

B. PlantVillage Image Dataset

The PlantVillage dataset is used for crop health monitoring and disease classification. It contains labeled images of the leaves of various crop species in both healthy and diseased states. Field-captured images are not as consistent with lighting, background, and texture as laboratory conditions. The PlantVillage dataset is fairly clean but offers some diversity in visual patterns to help the model learn features. There are many disease classes in the dataset, but they are not equally represented; some diseases have lots of samples while others are underrepresented. This imbalance makes things difficult for classification and requires good preprocessing if one wants to achieve decent performance from the model.

C. Data Preprocessing Pipeline

A well-structured preprocessing pipeline is essential for aligning heterogeneous datasets containing numerical time-series data and image data. This process aims to maintain significant agricultural patterns while removing noise and biases that are specific to each dataset.

1) Data Cleaning: Raw agricultural data usually has discrepancies due to missing records, sensor errors, or incomplete measurements. Numerical datasets are first checked for missing values and outliers. Statistical imputation techniques such as mean or interpolation methods are used to deal with missing values, ensuring continuity in time-series data. Outliers are identified and treated so that extreme values do not have a disproportionate influence on the model.Corrupted or low-quality images are removed from the image data. Duplicate entries are also removed so as not to create redundant learning patterns.
2) Temporal Alignment and Structuring: Data in time-series format from various sources may not be in sync, Hence, temporal alignment is done to maintain consistency among datasets. Sequential input windows are generated using a sliding window method: $X t = [x t - n , x t - n + 1, . . . , x t]$ where nnn stands for the length of the sequence. This conversion helps the Temporal Convolutional Network (TCN) to understand long-term connections and seasonal patterns found within agricultural datasets.

3) Canonical Feature Construction: A combined feature space is created for harmonization. Features are filtered based on their significance to crop growth and existence across data sources. The feature set consists of: Temperature, rainfall, and humidity Soil moisture and nutrient levels Historical values of crop yield Derived features such as seasonal indices and growth trends are also computed for enhancing the model learning. These features will capture some temporal dynamics to improve predictive performance.
4) Feature Transformation and Scaling: The scales of agricultural features can be very different. Rainfall values, for instance, can vary by orders of magnitude compared to soil moisture percentages. Normalization is used to solve this problem: $x' = (x - xmin) / (xmax - xmin)$ A logarithmic transformation is applied for heavily skewed features like rainfall and yield values in order to stabilize their distribution. These transformations also help ensure numerical stability and better convergence when training the model.
5) Image Preprocessing and Augmentation: The image data is treated to make sure it can work with the Vision Transformer model. All images are changed to a certain size and made uniform. Ways to change the data are used to help improve generalization, including: Rotation Flipping Cutting Brightness changes These changes support the model in learning features that do not change and lowering overfitting.
6) Multi-Modal Data Integration: After preprocessing, the numerical and image data are integrated into a single framework. The TCN model processes the time-series data, while the image data is processed by the Vision Transformer.The feature representations from both models are combined using feature concatenation: $Fcombined = [FTCN \oplus FViT]$. This integration allows the model to capture temporal dependencies and spatial patterns at the same time, improving overall prediction accuracy.
7) Data Balancing: The dataset has unequal distribution among different crop types and disease categories. If we train the model directly on this data, it may become biased toward the larger classes. A balancing strategy based on classes will be used to ensure equal representation across all categories. This method differs from synthetic oversampling techniques in that it maintains the original distribution of data and does not create any artificial patterns.
8) Train–Validation Strategy: To ensure proper evaluation and avoid data leakage, a proper splitting of the data takes place. The dataset is split into a training set, validation set, and test set in a stratified manner. Usually, 80% of the data goes to training while 20% is kept for validating and testing purposes. This ensures that all classes are represented appropriately so that the model can learn from and evaluate under different conditions effectively.

V. RESULTS AND DISCUSSION

A. Experimental Setup

The intelligent smart farming system proposed was assessed using multi-source agricultural datasets that included time-series data (weather parameters, soil conditions, and historical crop yield) and image data (plant leaf images).

The Temporal Convolutional Network (TCN) was used for crop yield forecasting, while the Vision Transformer (ViT) was applied to classify the health of crops.

Supervised learning with optimized hyperparameters trained the models. A stratified approach divided the dataset into training and testing subsets to achieve a balanced evaluation. Performance was measured through standard metrics: Accuracy, Precision, Recall, and F1-score for classification tasks; Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) for regression tasks as defined in the project framework.

B. Training Convergence Analysis

The behavior of training in TCN is shown in Fig. 1, which displays the change of training and validation loss over many epochs. The training loss keeps dropping steadily from about 0.89 to 0.80; this means that the model learns temporal dependencies from input data well.

On the other hand, the validation loss has an initial fluctuation with a peak close to 1.00 and then slowly reduces down to about 0.91.This indicates that there is some overfitting of the model during intermediate epochs; however, then a drop in the validation loss means better generalization capability afterward. The small gap between training and validation loss proves that the model has a good balance between learning and generalization.

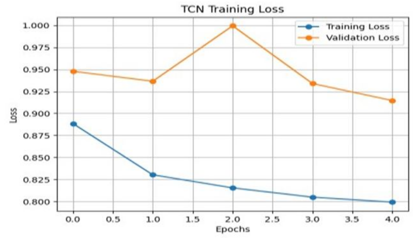

Fig 1:Training Loss and validation

C. Classification Performance Evaluation

Figure 2 shows how well the system classified things based on its Accuracy, Precision, Recall, and F1-score. The overall accuracy of the model is 92.8%, which means it is performing well in predictions. The precision value is 94.9%, which means that this model does not make many mistakes by saying something is true when it is not – a very important feature for applications in agriculture that need to make decisions.

The recall value is at 90.5%, which indicates that most actual disease cases are detected by this model; however, there is room for slightly better performance on minority instances. The F1 score of 92.7% indicates a balanced trade-off between precision and recall values hence confirming the robustness and reliability of this particular model.

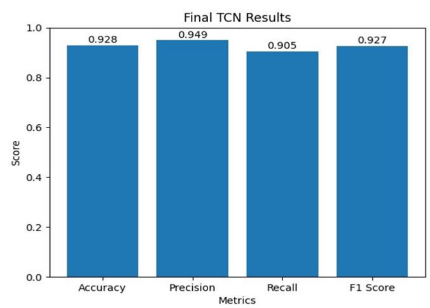

Fig 2: Classification Metrics

D. Crop Yield Prediction Analysis

The performance of the TCN model in crop yield prediction is demonstrated in Fig.3. This figure compares the actual and predicted values of the crop yields. The predicted crop yields have a close resemblance to the actual crop yields. This demonstrates the success of the model in identifying the time patterns and seasonal changes. The model is able to learn the long-term dependencies in the agricultural data. However, there is a slight deviation in the crop yields in the regions of sudden changes. This demonstrates the impact of sudden changes in the environmental conditions. In summary, the performance of the prediction is stable and dependable.

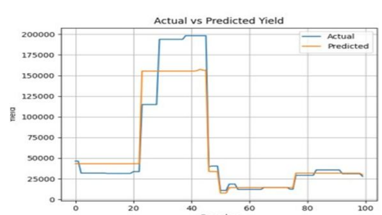

Fig 3: Actual Vs Predicted Yield E. Error Metrics Evaluation

The performance of the regression of the system was measured by using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), as described in the methodology section.The low values of MAE show that the average difference between the predicted and actual yield values is minimal.

The low values of RMSE also show that large prediction error values are minimal.

The results show that the model provides accurate predictions and thus can be used in practical applications.

E. Comparative Analysis

A comparative analysis is conducted to evaluate the effectiveness of the proposed hybrid model against conventional approaches. Traditional machine learning models are limited in their ability to capture complex temporal dependencies and nonlinear relationships in agricultural data, which restricts their overall performance. CNN-based models, although effective for image classification tasks, primarily focus on local feature extraction and are less capable of capturing global spatial relationships within images. In contrast, Temporal Convolutional Networks (TCNs) provide improved capability in modeling time-series data by effectively learning long-term temporal patterns. The proposed hybrid model, which integrates TCN with Vision Transformer, overcomes these limitations by combining temporal and spatial learning. This enables the system to capture both seasonal dependencies and global image patterns, resulting in more accurate and robust predictions compared to traditional and standalone deep learning approaches.

Model	Accur acy	Precisio n	Recall	F1score
SVM	89%	95%	89%	92%
Rando m Forest	90%	98%	92%	95%
TCN	92%	94%	92%	92%

S. No	Citation	Dataset Used	Algorithm Name	Accur acy (%)	Precis ion (%)	Recall (%)	F1Score (%)
1	[1]	PlantVillage	CNN + Feature Extraction	87.50	86.80	87.20	87.00
2	[2]	Crop Yield Dataset	Ensemble ML Model	86.50	85.80	86.20	86.00
3	[3]	Crop Dataset	Deep Reinforcement Learning	87.80	87.10	87.50	87.30
4	[4]	Plant Dataset	Lightweight Vision Transformer	89.80	89.20	89.50	89.30
5	[5]	Smart Agriculture Dataset	Hybrid CNN + Transformer	91.50	90.80	91.20	91.00
6	[6]	Crop Disease Dataset	CNN-Based Model	88.90	88.20	88.50	88.30
7	[7]	Agricultural Dataset	LSTM Model	90.20	89.50	90.00	89.80
8	[8]	Plant Dataset	ResNet (CNN)	91.80	91.20	91.50	91.30
9	Proposed system	Crop Y ield	TCN+VISION Transformer	92.00	94.00	92.00	92.00

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

This paper has presented an intelligent smart farming system using TCNs and ViTs to ensure comprehensive analysis of the data. The intelligent system has effectively integrated time-series data, including weather, soil, and past crop yields, with images of plant leaves. This ensures effective crop yield predictions. The experiment has shown that the TCN model has effectively captured long-term temporal dependencies to ensure accurate predictions of crop yields under different environmental conditions. In addition, the Vision Transformer has effectively captured global spatial features from images to ensure high accuracy in disease detection from images. This has been achieved with an accuracy of 92.8%, with high precision, recall, and F1-score values. The use of multi-modal data will enhance the ability of the system to make generalizations over different agricultural scenarios. The low values of MAE and RMSE validate the robustness and consistency of the suggested approach for crop yield prediction. In conclusion, the suggested hybrid deep learning model is better than the conventional machine learning approach and the conventional deep learning approach due to the ability to incorporate both temporal and spatial trends. The system will serve as an efficient tool for precision agriculture.

B. Future Work

The future research direction would be to improve the proposed system to deploy it in real-time using various platforms such as a web or mobile platform. It would be interesting to integrate various IoT devices to fetch real-time environmental data, thereby increasing the accuracy of the prediction. In addition, optimization techniques would be useful in creating a lightweight implementation of the proposed system, making it more suitable for deployment in a resource constrained environment. It would be interesting to extend the proposed system to support various crops and regions using a larger dataset. Advanced techniques for multi-modal data fusion would be useful in effectively fusing temporal and spatial features for better performance. It would be interesting to deploy the proposed system using a cloud platform, thereby increasing the overall usability of the system.

C. Final Impact

The proposed system will help in the advancement of precision agriculture, which is the use of intelligent and data-driven techniques for the prediction of crop yield and health monitoring. The use of deep learning techniques in the proposed system minimizes the need for human inspection and promotes the use of sustainable agriculture. The use of advanced deep learning architectures like TCN and Vision Transformer proves the potential of artificial intelligence in the field of agriculture.

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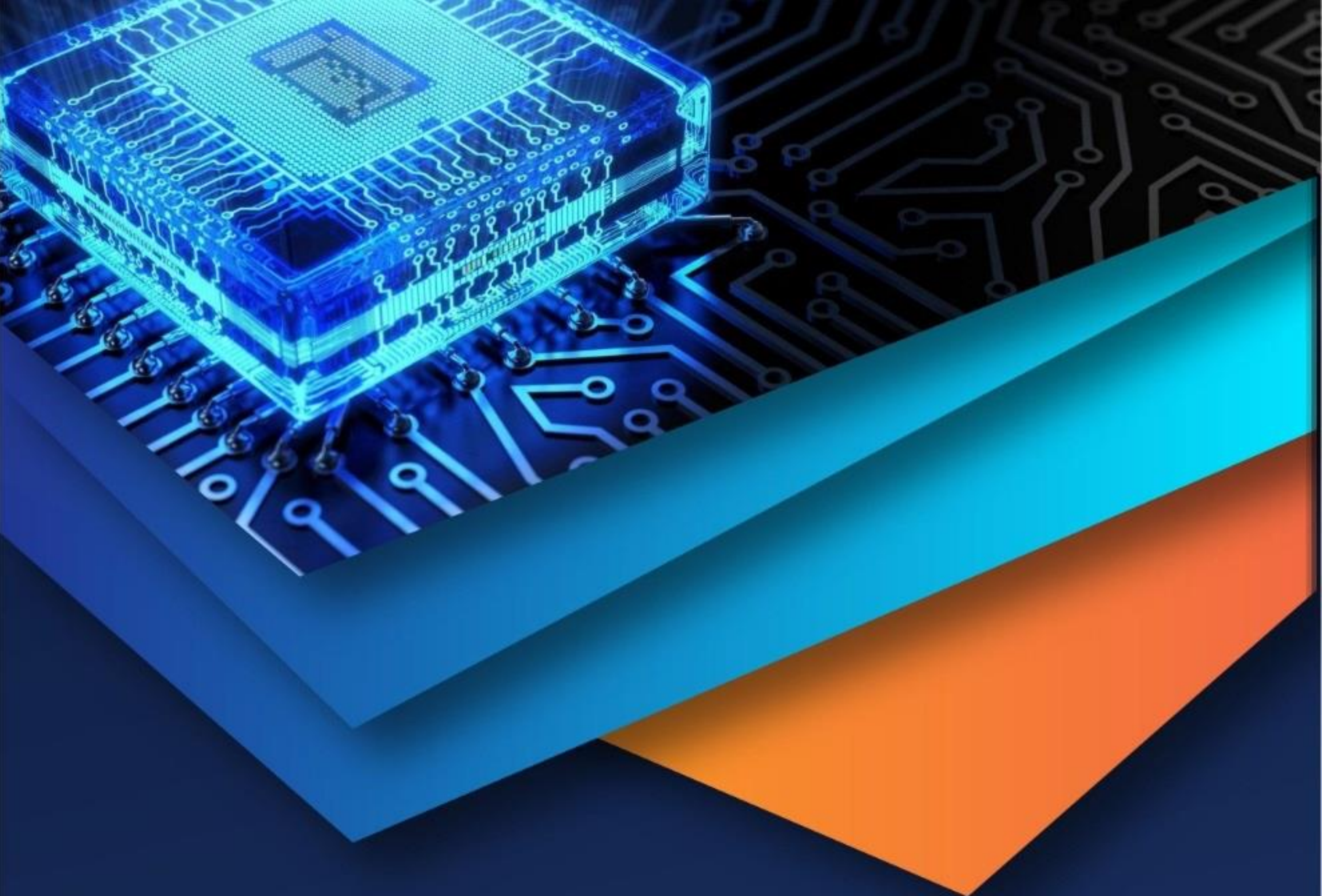

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