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Tomato Leaf Disease Detection Using Deep Learning

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Abstract: This project will build a machine learning solution for Detection of common diseases of tomatoes from a strong dataset of leaf photographs. We train deep models such as Convolutional from Kaggle. CNNs, MobileNet, and ResNet are employed for leaf condition classification. The system detects diseases such as Tomato Mosaic Virus, Target Spot, Early Blight, and Late Blight, Bacterial Spot and Septoria Leaf Spot with healthy leaves. The backend, Pythonbased, processes the user images and offers real-time Predictions. The frontend, which is built with HTML, CSS, and JavaScript, is intuitive. Interface that allows farmers and gardeners to monitor and diagnose easily tomato plant health, increasing crop management and yield.

Keywords: Tomato leaf diseases, Deep learning, Convolutional Neural Network(CNN), MobileNet, ResNet, Python, Tomato plant disease, Plant disease detection, Tomato health monitoring, Agricultural Technology, Image Classification.

I. INTRODUCTION

Tomato plants are highly vulnerable and extremely susceptible to a wide range of diseases, which can drastically affect the yield as well as the overall quality of the crop. Early identification of these diseases is essential in preventing largescale destruction that would destroy the harvest, and also plays a significant role in enabling efficient management methods in crop cultivation. Conventionally, disease identification has depended to a large degree on manual inspection methods, which are generally time-consuming, prone to errors, and provide inconsistent outcomes. To overcome these limitations efficiently and improve the process, this project employs cutting-edge deep learning techniques to design an advanced automated system specifically for the identification of leaf diseases in tomatoes[1].The system utilizes stateof-the-art technology in the guise of Convolutional Neural Networks, popularly known as CNNs, and some architectural styles known as MobileNet and ResNet[2]. The combination of this powerful technology results in the system being able to systematically classify tomato leaf images into different classes depicting different diseases[3]. The most common diseases detected through this classification include the Tomato Mosaic Virus, Early Blight, Late Blight, Target Spot, Bacterial Spot, and there is a specific class for healthy leaves with no sign of any disease[4]. From a technical standpoint, the backend of this high-tech system has been developed utilizing the very adaptable Python programming language.This programming language is well suited for the handling of intricate image processing processes while at the same time facilitating stable model predictions[5]. Meanwhile, the frontend of the application has been developed using state-of-theart web development technologies, namely HTML, CSS, and JavaScript[6]. These technologies in combination create an interactive and user-friendly interface that enables users to easily upload images of their tomato plants and instantly receive results concerning the health status of the aforementioned plants[7].

With the combination of cutting-edge deep learning techniques and an easy-to-use interface, this new project is constructed with the aim of providing a highly efficient, remarkably accurate, and easily accessible solution solely for identifying diseases that may develop on the leaves of tomatoes. This comprehensive system will benefit farmers as well as agricultural specialists in making judicious decisions, which in turn will result in a significant reduction in crop loss and considerable enhancement in overall agricultural output in various farming operations.

II. LITERATURE SURVEY

Deep learning came strongly to plant disease detection in the past decade as a result of the necessity for accurate, scalable, and automated diagnosis in agriculture. Mohanty et al. (2016) led the breakthrough with their work, which confirmed the effectiveness of Convolutional Neural Networks (CNNs) over traditional machine learning algorithms in image-based plant disease diagnosis. Their model achieved record-breaking accuracy levels of over 98%, setting the stage for the next wave of research.

Ferentinos (2018) later confirmed the effectiveness of CNN-based architectures, showing that they withstood the test of distinguishing a wide range of plant diseases under varied conditions. These studies provided the foundation for the application of deep learning in plant disease diagnosis.

Refinements were also made with the exploration of specialized neural network architectures. Too et al. (2019) contrasted the performance of fine-tuned deep learning models and noted that MobileNet stood out as particularly well-suited to realtime disease detection due to its light architecture and minimal computational needs. This was a breakthrough finding for model deployment in resource-constrained environments, such as edge or mobile devices. He et al. (2016) otherwise led the field with the identification of Residual Networks (ResNet), which addressed the challenge of training extremely deep networks with new skip connections. This architecture significantly improved classification accuracy and was a precursor to much of the following work. The comparative review by Zhang et al. (2020) gave a comprehensive evaluation of these advances, describing ResNet as the top-performing model for plant disease diagnosis but validating MobileNet's suitability for real-time deployment. Together, these papers chart the evolution of deep learning techniques in plant pathology from initial proof-of-concept demonstrations to the development of effective, deployable systems. Deployment of these technologies in crop production can enhance crop monitoring, reduce yield loss, and facilitate sustainable farming practices. Future research areas could involve improving model interpretability, expanding datasets to cover rare diseases, and further optimizing architectures for global deployment.

III. METHODLOGIES

A. Modules

1) Data Preprocessing Module

Loads the tomato leaf dataset and proceeds to preprocess it for analysis.Utilizing different methods like image resizing, normalization, and augmentation methods, including rotation, flipping, and brightness adjustment, among others, with the goal of enhancing the performance of the model considerably.It Divides the dataset into three sets i.e.,training, validation, and testing set.

2) Model Training Module

Utilizes deep learning models: CNN, MobileNet, and ResNet for image classification.The procedure involves model training from the dataset to ensure that effective hyperparameters are used, some of which include the learning rate, batch size, and epochs.Uses various modern methods, including transfer learning and model fine-tuning, to achieve a higher level of accuracy and precision in outputs.

3) Backend Module

Loads the trained model and performs inference (prediction) on uploaded images.Installs the API endpoints required for effective communication and data exchange between the frontend user interface and backend server infrastructure.Processes the images uploaded by the users and then returns the results of disease classifications from the images.

4) Frontend Module

It Offers a basic and easy-to-use interface through which users can simply upload tomato leaf images.Illustrates real-time classification by displaying the names of the diseases that have been correctly classified. It Provides a design that is not only simple to comprehend but also highly user-friendly, and this enhances the overall user interaction experience greatly.

5) Deployment Module

Successfully deploys the trained model to a complete web application.Uses a number of cloud platforms like Amazon Web Services (AWS), Heroku, or Google Cloud to deploy the application effectively and in a scalable manner.ItEnables scalability and access to farmers and agricultural experts.

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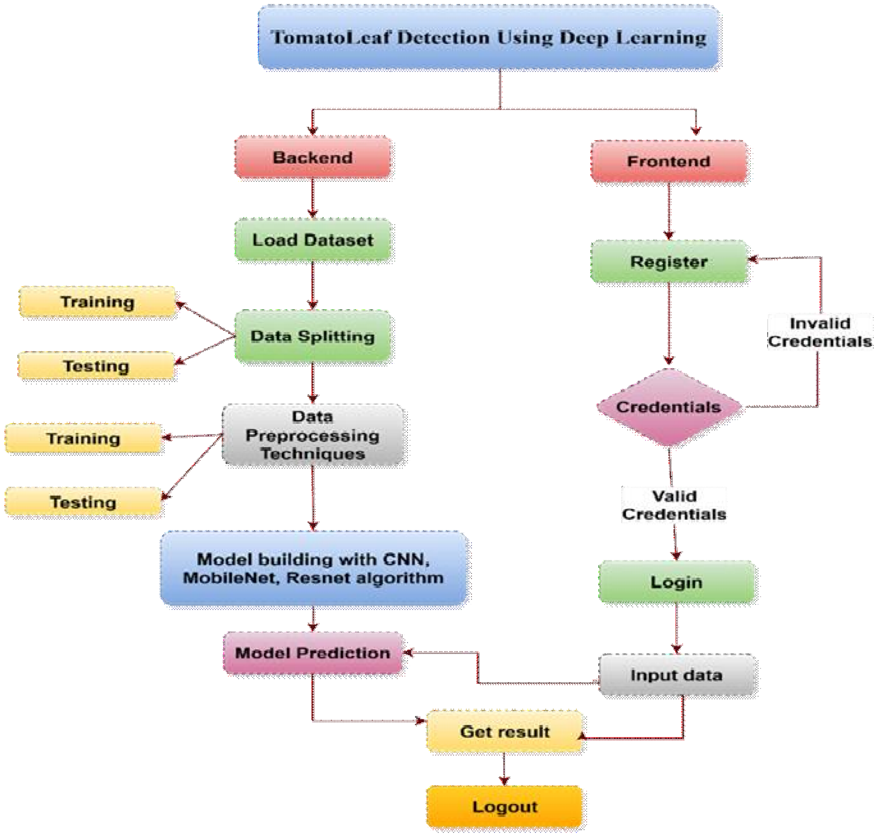

Fig.1 Project Flow

B. Algorithms Used

RESNET(RESIDUAL NETWORK) ALGORITHM: ResNet is a deep neural network architecture that avoids the vanishing gradient issue in deep networks. It employs skip connections to allow information to skip layers, thus simplifying learning. ResNet learns the residual mapping rather than the direct mapping, improving optimization and gradient flow. This allows very deep networks such as ResNet-50, ResNet-101, and ResNet-152 to be trained without compromising performance.

ResNet is extensively applied in image classification, object detection and medical imaging because of its reliability and accuracy. ResNet is utilized in this project in combination with CNN and MobileNet to improve the detection and classification of tomato leaf diseases to deliver consistent plant disease detection.

CONVOLUTIONAL NEURAL NETWORK(CNN) ALGORITHM: Convolutional Neural Networks, or CNNs, are a highly specialized type of deep learning model architecture that is specifically suited for image recognition and image classification problems. As compared to conventional machine learning models, which are prone to needing significant feature engineering, CNNs possess the remarkable capability to automatically discover useful features directly from images in a complex sequence of convolutional, activation, and pooling layers. The function of the convolutional layer is central to this task because it is tasked with detecting simple patterns in the images, including edges, textures, and shapes.

At the same time, the ReLU activation function is used to add non-linearity to the model, greatly improving the learning capability of the network by enabling it to recognize intricate relationships. Moreover, the pooling layers also play a critical role by reducing the spatial dimensions of the data, thereby making the network efficient and responsive to processing data at a faster rate. Lastly, the fully connected layers are tasked with classifying the extracted features and mapping them to different classes based on the identified patterns throughout the network. CNNs perform better than the conventional models as they minimize the requirement for manual feature extraction and enhance the precision of classification. They are extremely efficient in medical imaging, agriculture, and security applications. CNNs, MobileNet, and ResNet are applied in this project to classify different diseases of tomato leaves, and it is an accurate and automatic disease detection system for enhanced agricultural productivity.

MOBILENET ALGORITHM: MobileNet is a deep learning model for low-resource mobile and edge devices, such as smartphones and IoT. It achieves effective neural networks by using light-weight depthwise separable convolutions.

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Convolutional layers do full convolutions for every input channel in the traditional method, which is expensive. MobileNet replaces it with a depthwise convolution using a single filter per channel and a pointwise convolution to combine them. This reduces parameters and expense, so MobileNet is far more efficient than regular convolutional networks without compromising on image classification and other applications. MobileNet architecture uses a width multiplier to control model size and computational requirements.A low multiplier reduces filters per layer, creating a lean, quicker model at the cost of some accuracy. It's extremely widely used for real-time applications like object detection, face recognition, and image classification, trading off speed and accuracy on resource-limited hardware. Its efficiency makes it developers' first choice for deploying machine learning in power-limited devices.

C. Dataset

Class Name	Pathogen/causes	No.of Images	Key Visual Symptoms
Tomato Late blight	Oomycete	1,005	Irregular,water-soaked Lesions with white fungal under humid condition.
Tomato healthy	-	1,100	Uniform green color,no spots or discoloration.
Tomato Early blight	Fungus	1,100	Concentric dark rings with yellow halos.
Tomato Septoria leaf spot	Fungus	1,100	Small,circulargray-white spots with dark edges, often on lower leaves.
Tomato yellow leaf curl virus	Virus	1,100	Upward leaf curling, yellow margins,stunted growth.
Tomato Bacterial spot	Bacteria	1,100	Small, greasy, angular spots with yellow halos.
Tomato target spot	Fungus	1,100	Brown spots with light centers, resembling target rings.
Tomato mosaic virus	Virus	1,100	Mottled green/yellow mosaic patterns, leaf distortion.
Tomato Leaf Mold	Fungus	1,100	Pale green/yellow patches with purple-graymold underneath.
Tomato Spider Mites	Mite	1,100	Fine webbing, stippling(tiny white/yellow dots) on leaves.

Table. 1 Dataset description

IV. EVALUTION METRICS

The important Performance Metrics for Tomato Leaf Disease Detection to show the performance of our proposed models. Several metrics are calculated including accuracy, precision, recall and F1 score .which offers a complete perspective of our selected models's performance.

1) Accuracy:

$$\text{Accuracy} = \frac{TP+FN}{TP+TN+FP+FN} \times 100\%$$

Where,

TP (True Positives): Correctly predicted diseased leaves.

TN (True Negatives): Correctly predicted healthy leaves.

FP (False Positives): Healthy leaves misclassified as diseased.

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FN (False Negatives): Diseased leaves misclassified as healthy.

2) Recall:

$$\text{Recall} = \frac{TP}{TP+FN}$$

3) Percision:

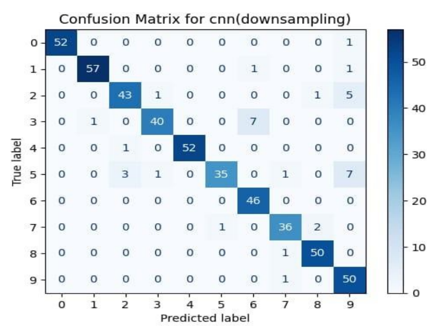
$$\text{Percision} = \frac{TP}{TP+FP}$$

4) F1-Score:

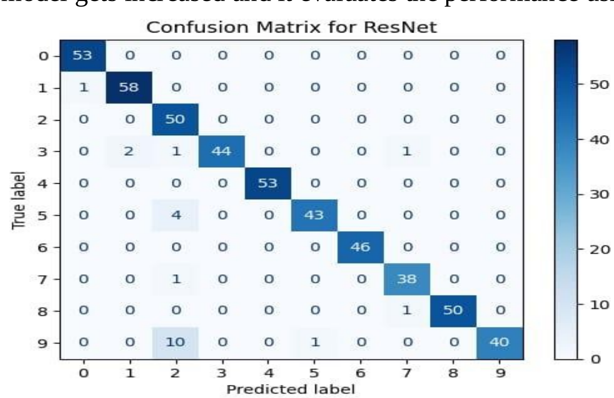
$$\text{F1} = 2 \times \frac{Percision \times Recall}{Percision + Recall}$$

V. RESULTS AND ANALYSIS

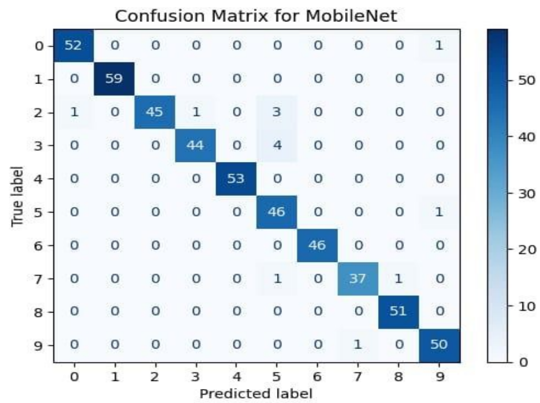
Using of CNN can help for automatic feature extraction by using the Leaf color variations, spots, fungus, shape deformation. It has a capability to handle with various light variations, we as the datasets that are trained by using the pre trained models like ResNet,MobileNet.The CNN forms a confusion matrix between True labels and predicted lables in order to evaluating the performance of a model. It checks both the ResNet and MobileNet Models and find out which is the best model among them in order to increase the accuracy and performance of a model.



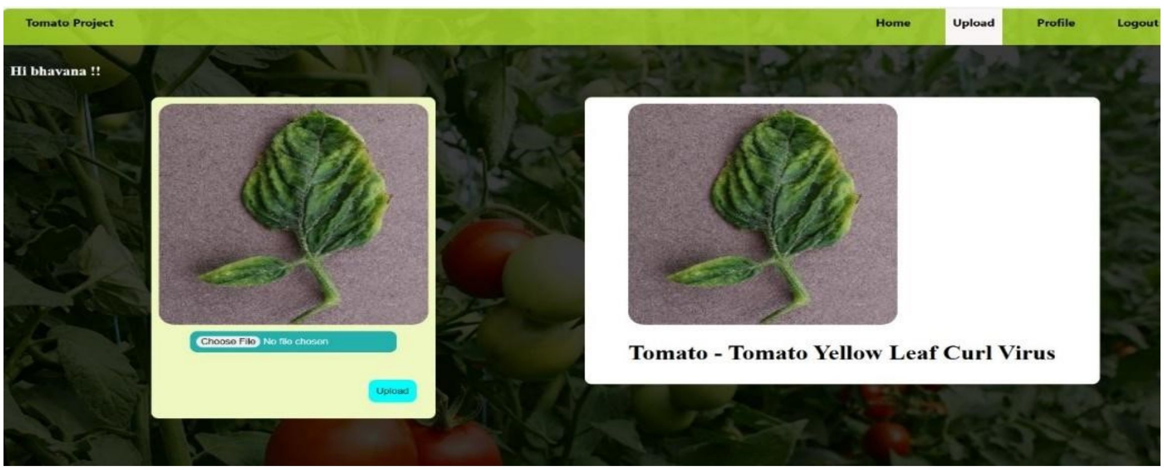
The Resnet model is used to increase the performance of the CNN model,theResNet model works on the given layers i.e, when we increase the layers the performace of model gets increased and it evaluates the performance using confusion matrix.



MobileNetis a lightweight CNN architecture designed for fast and efficient performance and it is worked using three layers in order to detect colors,shapes,patterns and spots. It is evaluated by using the confusion matrix of the dataset.



By taking the trained image as input we upload the image and compare with the dataset to find out the disease of tomato leaf.



When compared to both ResNet and MobileNet models, The MobileNetachive higher accuracy and better performance than ResNet.

VI. CONCLUSION

This project effectively deploys a deep learning-based system for the detection of tomato leaf diseases using CNN, MobileNet, and ResNet architectures. Based on an image dataset of tomatoes leaf, the system effectively diagnoses tomato leaf diseases like Tomato Mosaic Virus, Tomato Target Spot, Tomato Early blight, Tomato Late blight, Bacterial Spot, and Septoria Leaf Spot, among others. The Python-based backend facilitates effective model inference, while the HTML, CSS, and JavaScript frontend offers a user-friendly interface for easy disease diagnosis.

The system suggested works to overcome the various shortcomings and drawbacks of the conventional disease detection approaches by coming up with a solution that offers significantly quicker, more precise, and scalable forms of disease detection. The solution offers a way to significantly aid farmers, crop scientists, and plant health specialists by allowing them to make on-time and sound judgments that will be able to avert loss of crops and ultimately enhance the quality of the overall yield in the long run. Future progress can involve integrating real-time detection functionality through mobile applications, along with integrating the system with IoT-based monitoring systems for agriculture, giving rise to an even stronger and automated tool of effectively controlling disease.

VII. ACKNOWLEDGMENT

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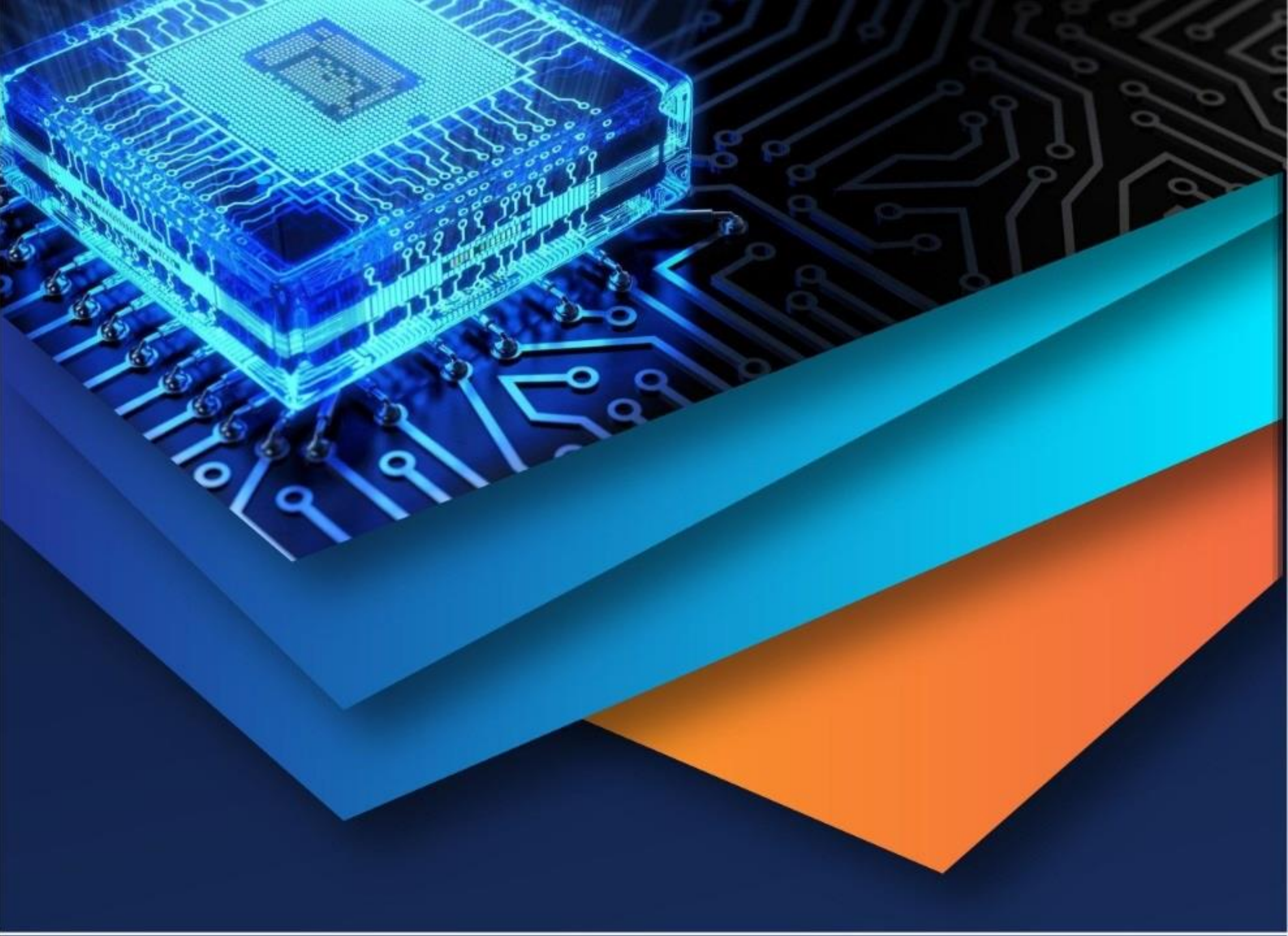

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