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Android Application Based Real-Time Plant Disease Detection and Remedy Suggestion System using Machine Learning

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Abstract: As crop diseases are major threat to food security, the detection and quantification of these diseases using ICT enabled technologies is an important research frontier. New and accurate methods would be an asset to farmers, for whom early disease detection can mean the difference between successful intervention and massive losses, and plant breeders, who often must rely on time-consuming phenotyping by naked eye. In view of this, in this paper, we have proposed an android application assisted disease diagnosis and remedy suggestion tool. We aim at developing an efficient, scalable, and accessible tool for plant disease detection, classification, and remedy suggestion using machine learning. The system facilitates farmers to instantly and accurately identify diseases and get solutions with an android app simply by photographing affected plant parts. A Convolutional Neural Network (CNN) model is designed and developed to diagnose test images. U-Net classifier algorithm, is modified and trained on public dataset containing images of diseased and healthy plants of grape and cotton, under controlled conditions. Once trained, it detects and classifies the disease of the test images of the plants fed to the U-net with an accuracy of 96.8%. In addition to this, we have also implemented a language translation feature by providing three language options- English, Hindi, and Marathi in android application to facilitate farmer for friendlier user interaction. As an advisory support to farmers, plant care tips are also incorporated as an additional feature.
Keywords: Plant disease detection and classification, machine learning, convolution neural network (CNN), U-Net classifier, model ensemble, android application, language translation, remedy suggestion.

I. INTRODUCTION

India is the world's largest producer of various ranges of commodities due to its favourable agro-climatic conditions and rich natural resource base. Significant achievements have also been made in increasing yield and production through development of high yielding varieties, appropriate transfer of technology, and better farm management practices [1]. Therefore, the Indian agriculture export has been occupying the place of pride in the export market. However, the quality of the produce has not been improved significantly. India has been exporting low quality and importing high quality produce up until the early 2000s. Several factors such as sudden climate changes, plant diseases caused by pests, rodents, and microorganisms, erroneous agricultural practices, etc. are responsible for producing low quality cotton and grapes [2].

Manual identification of diseases is labour intensive, less accurate and can be done only in small areas at a time. In contrast, computer vision algorithms can be used to provide image-based automatic inspection with quick and accurate results for large areas. By this method, plant diseases can be identified at initial stage itself and specialized control tools can be used to solve pest problems while minimizing risks to people and the environment [3].

In this paper, an attempt has been made to provide a fast, and practical solution for detecting plant diseases and also for providing remedial suggestions along with general advisory plant care tips. A CNN model is modified for detection of plant diseases. It uses simple leaf images of healthy and diseased plants, through deep learning methodologies. Training of the model was achieved with the use of a public database of grape and cotton plants. A model is trained such that it can achieve high success rate in identifying the corresponding diseased (or healthy) plant. A high success rate will make the model a very useful advisory or early warning tool, and an approach that could be further expanded to support an integrated plant disease identification system to operate in real cultivation conditions.

The paper is organized as follows: Section II gives review of literature. Section III describes the diseases of grape, and cotton plants. Section IV gives the designed and developed methodology. Section V evaluates experimental results. Finally, Section VI provides the paper's conclusion and scope for future works.

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II. REVIEW OF LITERATURE

Dhakate et al. in [4] have classified and detected four pomegranate diseases named as bacterial blight, fruit spot, fruit rot and leaf spot using Digital Image Processing and Artificial Neural Network (ANN) technique. The images acquired from farms are collected in an image database and pre-processed. Segmentation is done using k-means clustering based colour segmentation technique, feature extraction using Gray level co-occurrence matrix (GLCM) method and finally the training of the ANN using Back propagation Algorithm. Sardogan et al. in [5] has proposed a Convolutional Neural Network (CNN) model with Learning Vector Quantization (LVQ) algorithm-based method for tomato leaf disease detection and classification. The proposed method classifies the given images between healthy and diseased. The result validated on a large dataset shows the accuracy of the deep learning approach. CNNs have been proposed by Singh in [6] for the real-time classification of the disease from the plant leaf images. The proposed method is built on a cloud-based environment for performing this task. The images of the plant leaves are collected in the real-time for classification using the Inception model as classifier. The overall accuracy of this model is 95%. Singh et al. in [7] have proposed a Multilayer Convolutional Neural Network (MCNN) for the classification of Mango leaves infected by the Anthracnose fungal disease. The results are compared with other state-of-the-art approaches named as Particle Swarm Optimization (PSO), Support Vector Machine (SVM), and Radial Basis Function Neural Network (RBFNN). The accuracy of the proposed method was computed to be 97.13% which is higher than other classification methods. VGGNet with the Inception module is used to improve the extraction performance and then Rainbow concatenation method is integrated in Single Shot Detector for the deep learning network by Jiang et al. in [8] for the classification of apple leaf diseases. Furthermore, the authors have demonstrated multiple techniques for the augmentation of data to solve the issue of insufficient images and prevent overfitting of the CNN-based model in the training process. Vaishnnave et al. [9] have worked with k-Nearest Neighbour (KNN) for the identification of groundnut diseases like early leaf spot, late leaf spot, rust, and bud necrosis. The proposed method of the research by Rahman et al. in [10], focuses on improved segmentation approach for plant leaf disease identification. They have proven this by achieving an accuracy of 99.25% by using RGB threshold and Morphological operation technique for image segmentation. Militante et al. [11] have presented a study of deep learning in plant pathology. The proposed method classifies the given images between healthy and diseased. The result was validated on a large dataset of approximately 35,000 images containing 9 types of tomato leaf diseases, 4 types of grape leaf diseases, 4 types of corn leaf diseases, 4 types of apple leaf diseases, and 6 types of sugarcane diseases. This model shows the accuracy of 96.5% for the deep learning approach. Sinha et al. [12] have presented two different approaches to image segmentation technique consisting of thresholding on the La*b* colour histogram values and k-means clustering for the *Neofabrea* leaf spot disease of the Olive Plant. The thresholding technique shows high efficiency, but k-means shows better results overall. Sharma et al. in [13] have presented various studies of algorithms used for the identification and classification of the disease from the leaf images of the plant. This work compares various algorithms like Logistic regression, k-Nearest Neighbour (KNN), Support Vector Machine (SVM) and Convolutional Neural Network (CNN). CNN outperforms all others with an accuracy of 98%.

III. DESCRIPTION OF PLANT DISEASES

A. *Grape Diseases*

1) *Alternaria blight*: The disease attacks both leaves and fruits. Small yellowish spots first appear along the leaf margins, which gradually enlarge and turn into brownish patches with concentric rings which can lead to drying and defoliation of leaves if severe infection occurs. Dark brown-purplish patches appear on the infected berries. It is shown in Fig. 1(a).
2) *Anthracnose*: First symptom appear in the form of dark red spots on the berry. Later, they turn into circular, sunken, ashy-grey and in late stages these spots are surrounded by a dark margin. It is shown in Fig. 1(b).
3) *Powdery Mildew: Powdery mildew can infect all green tissues of the grapevine. Diseased leaves appear whitish grey, dusty, or have a powdery white appearance. If infection occurs in younger berries, they dry up or rot. When older berries are infected, a netlike pattern often develops on the surface of the berry. It is shown in Fig. 1(c).*
4) *Downy Mildew: The fungus attacks all green parts of the vine. Infected leaves develop pale yellow-green lesions which gradually turn brown. Severely infected leaves often drop prematurely. It is shown in Fig. 1(d).*

B. *Cotton Diseases*

1) *Bacterial Blight:* Bacterial Blight starts as small, water-soaked spots on leaves and can be observed on seedlings as well as mature plants. They turn black as they age and increase in size. It is shown in Fig. 2(a).
2) *Alternaria Leaf Spot:* On green leaves there is pronounced purple coloured margin all around the spot. On older leaves, the spot is often marked by a pattern of concentric structure. In humid weather conditions, the necrotic tissues turn a sooty black colour due to prolific sporulation by the fungus. It is shown in Fig. 2(b).

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3) *Leaf Rust:* The disease is characterized by reddish brown colourations scattered over the whole green surface of leaves. These spots coalesce to turn into large patches. It is shown in Fig. 2(c).
4) *Fusarium Wilt:* In young and grownup plants, the first symptom is yellowing of edges of leaves and area around the veins. The leaves lose their turgidity, gradually turn brown, droop, and finally drop off. Black streaks or stripes may be seen extending upwards to the branches and downwards to lateral roots. It is shown in Fig. 2(d).

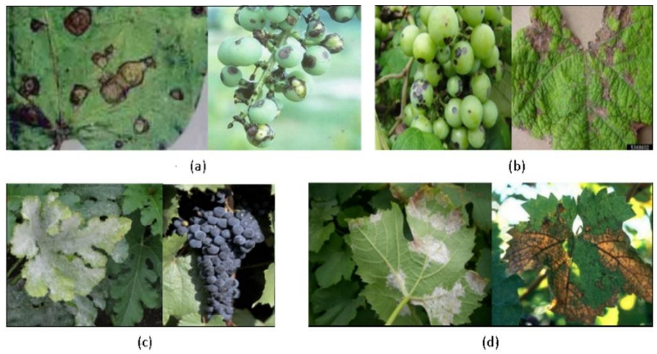

Fig. 1.(a) Alternaria blight (b) Anthracnose (c) Powdery mildew (d) Downy mildew

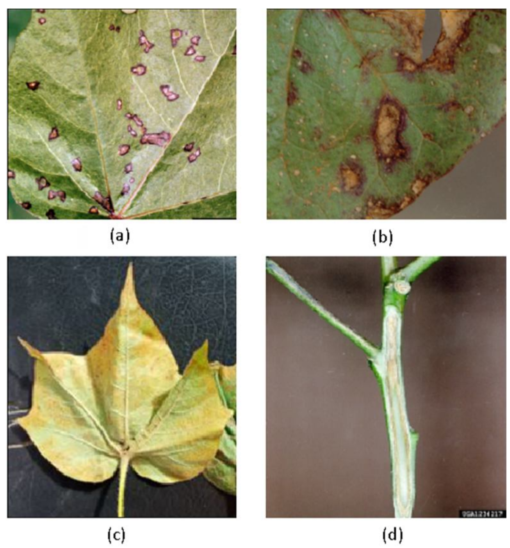

Fig. 2.(a) Bacterial blight (b) Alternaria leaf spot (c) Leaf rust (d) Fusarium wilt

IV. METHODOLOGY

A. Dataset and Pre-Processing

In the proposed work, plantVillage dataset [14] repository, having leaves of multiple plants, has been used. A total of 5000 images comprising 3000 Grape images and 2000 Cotton images are used to train and test the model. We have categorized these images into two classes namely leaf images with the disease, and leaf images without the disease, for each type of plant.

Before the classification of the images from the data set repository takes place, the image is first annotated and augmented i.e., the image data needs to undergo pre-processing.

In image annotation, the features of an image are identified and accordingly image labelling is carried out. It helps to train the machine learning model. As, manual image annotation is time-consuming, hence, we have employed an automatic image annotation process in which computer automatically assigns metadata to a digital image (captions or labels), using relevant keywords to describe its visual content [15].

Afterwards, image augmentation is performed to artificially expand the size of the training dataset by modifying the already available images. We have done this by using population-based augmentation technique. The images are rotated, sharpened, brightened, inverted, etc.

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B. Segmentation and Classification

To reduce the size of the images, segmentation is essential. However, it can often be time consuming, thus for better performance we made use of U-Net [16].

The network architecture is illustrated in Fig. 3. It consists of a contracting path (left side) and an expansive path (right side). The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. At each downsampling step we double the number of feature channels. This downsampling process is done for feature extraction. In contrast to this, every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution ("up-convolution") that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer a 1x1 convolution is used to map each 64-component feature vector to the desired number of classes. In total the network has 23 convolutional layers [17].

To allow a seamless tiling of the output segmentation map, it is important to select the input tile size such that all 2x2 max-pooling operations are applied to a layer with an even x- and y-size. The pre-processed dataset consisted of images of width: 256 pixels and height: 256 pixels. However, to accommodate all types of image sizes, we have used a function which can upscale or downscale the image as per the model's requirement.

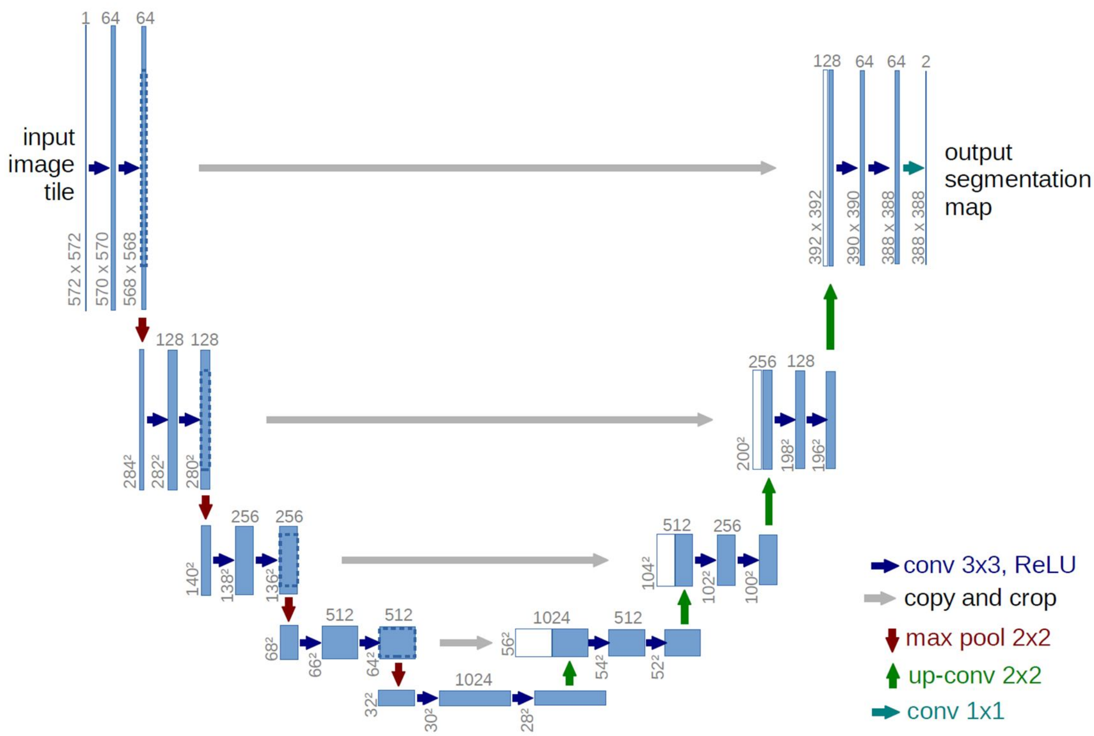

Fig. 3.U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

The mobile app contains a simplified frontend for the farmer that is easy to use and hides the complexity of the backend. It enables the user to take images of the plant (live mode) or choose existing images from the gallery (offline model). It allows them to get the disease type of the uploaded images with a score reflecting the degree of accuracy of classification along with its remedial solution. Android Studio 3.1.3 Is used to develop the mobile app in Java. Fig 6 shows the expected output which gets shown on user screen in real time.

C. Flow of Execution of the App

1) The application loads up.
2) If the internet is active, internal functionality calls the server to check any changes in model.
3) If there are changes, it downloads the new model and updates itself in the background.
4) User taps on the capture button to collect an image from the field.
5) Image gets sent to an ‘edit’ method, which can crop the image, and enhance it as user wishes.
6) App prompts the user to ‘save’ or ‘revert’ changes, after which image gets sent to the ML model.
7) ML model up/down samples image size according to model’s requirement.
8) The image gets classified in categories after it is given as an input to the ML model, according to the dataset available.
9) After classification, a call to database API is made via app to get relevant remedy for the disease, if any.
10) Both the condition of the plant and remedy is shown on the screen.
11) Event of disease detection and course of action is saved in an in-app calendar.
12) The image and performance statistics get sent to the server, where it saves the files on cloud.

V. RESULTS AND DISCUSSION

The entire dataset is grouped in 3 sets of training data and testing data each as shown in Table I. All these images are chosen randomly.

TABLE I. Dataset split for Training and Testing

Training-Testing split in %	Training data	Testing data
80-20	4000	1000
70-30	3500	1500
60-40	3000	2000

TABLE II. Accuracy per Epoch

Training-Testing split in %	Accuracy in %			
	10 Epochs	*50 Epochs*	*100 Epochs*	*200 Epochs*
80-20	84.7	92.5	96.4	96.8
70-30	78	91	95.7	96.2
60-40	74	91	94	96

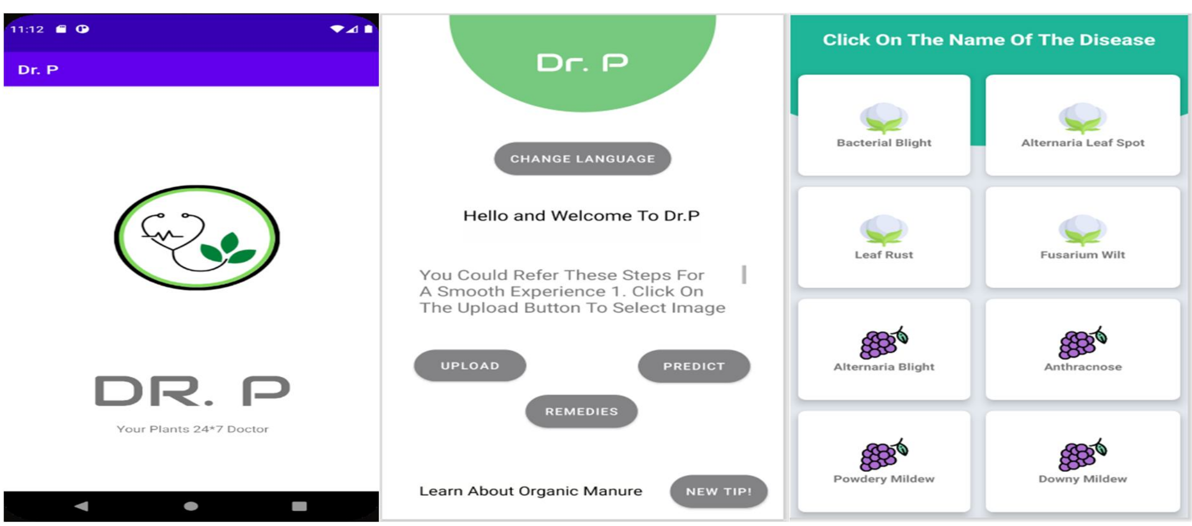

Fig. 4. Android application screen. (a) Loading screen (b) Dashboard screen (c) Language change feature screen

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The accuracy for each data split is shown in Table II. The data is given after every several epochs of training. However, in comparison with the other train-test dataset splits, the data split of 80%—20% performed very well at the epoch scale of 200 with the maximum accuracy of 96.8%.

In Fig. 5, accuracy is presented for each epoch. There is an exponential increase in accuracy as we increase training-testing split for interval 10-50 epochs for each dataset. It also shows that after 50 epochs, the change in accuracy reduces.

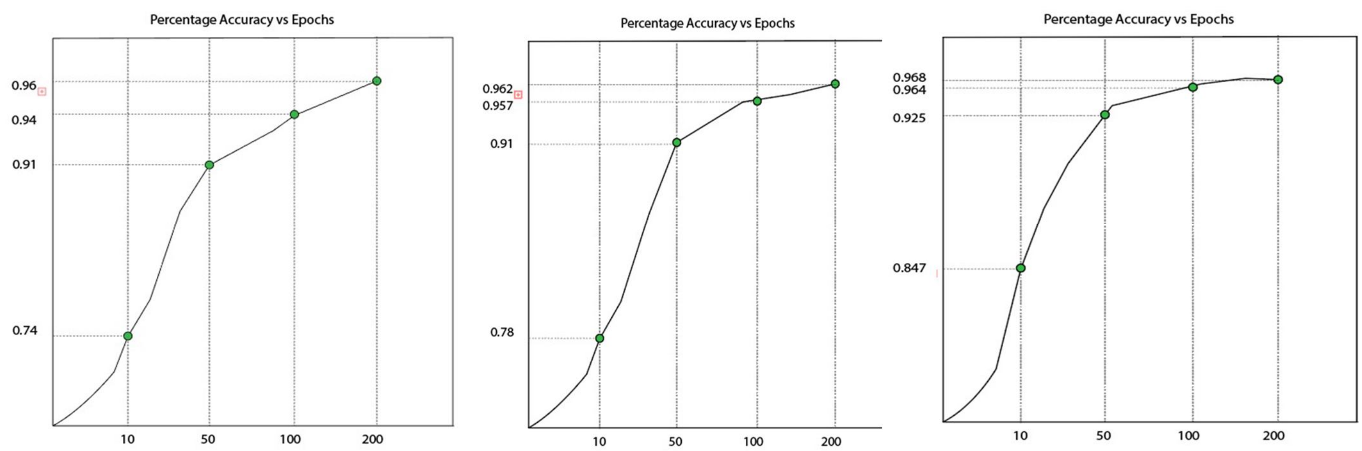

Fig. 5.Accuracy vs Epoch graph (a) 60%-40% (b) 70%-30% (c) 80%-20%

VI. CONCLUSION AND FUTURESCOPE

In this paper, we have successfully designed an android application assisted disease diagnosis and remedy suggestion tool. It efficiently detects, and classifies plant diseases, and suggests remedies using machine learning. Convolutional Neural Network based U-Net model is used to perform classification. The disease identification accuracy of the model is 97.3%. The optimal number of epochs is 120 in order to get the ideal accuracy with low validation error. The disease identification accuracy obtained after training the model for 120 epochs is 97.3% which is greater than 96.8% at 200, it is justified due to a phenomenon of overfitting and overtraining model performance may degrade, thus we stopped training at 120 epochs beforehand. In addition to this, the remedial solutions provided by the app can facilitate the farmers with accurate steps for treating the diseases. The technology can be further developed by adding more classes of crops. To improve its usability and applicability, the model can be incorporated into various other platforms such as iOS and Windows. It can be further extended by incorporating a time series model for classifying diseases based on weather and seasonal changes. Furthermore, the change language feature can be expanded to encompass other languages.

Fig. 6.Model outputs a bounding box on infected area

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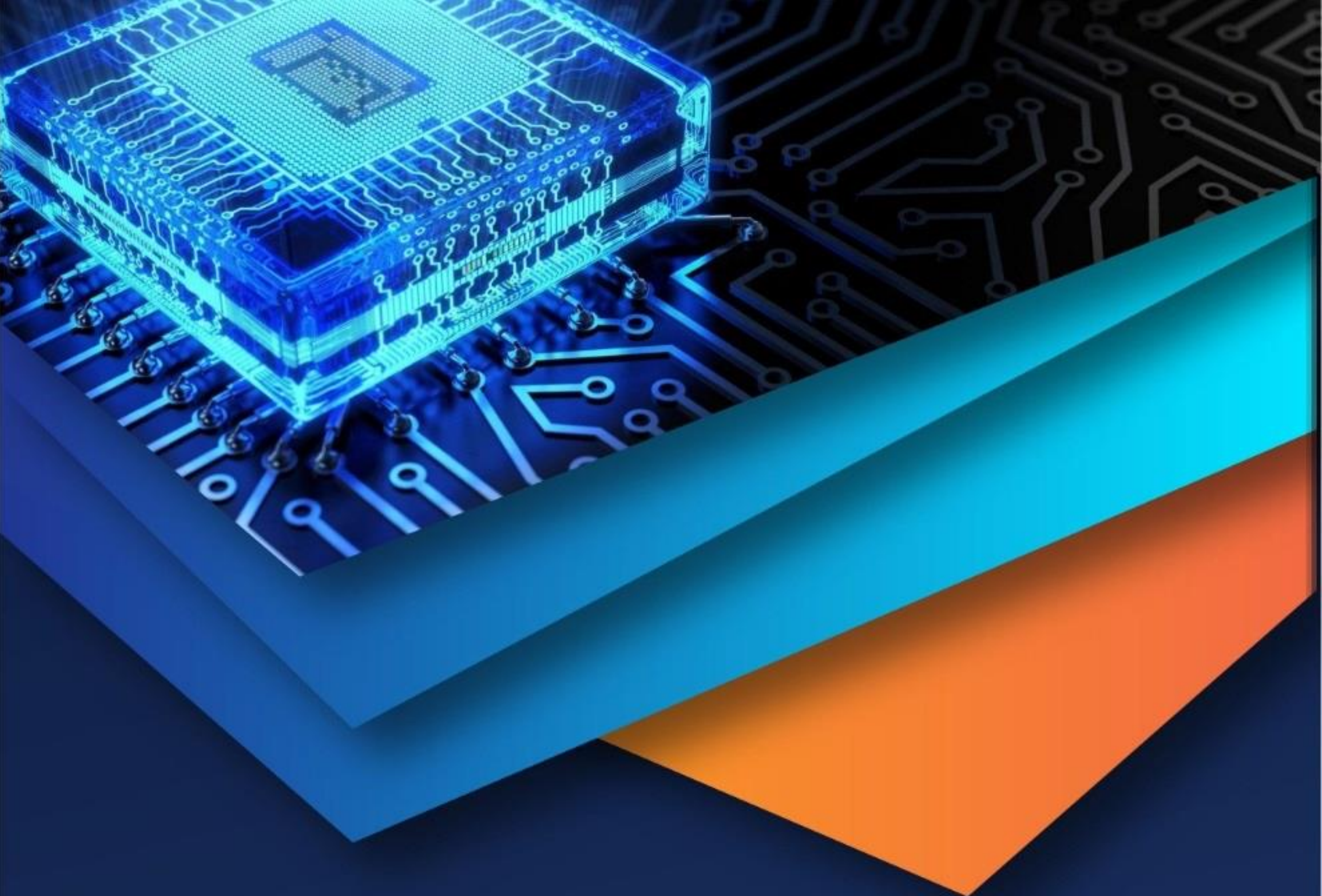

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