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Automatic Detection of Citrus Fruit and Leaves Diseases Using Deep Neural Network

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Abstract: Citrus fruit diseases are the major cause of extreme citrus fruit yield declines. Plant disease detection and classification are crucial long term agriculture. Manually monitoring citrus diseases is quite tough. As a result, image processing is used for designing an automated detection system for citrus plant diseases. Image acquisition, image preprocessing, image segmentation, feature extraction and classification are main processes in the citrus disease detection process. Deep learning methods have recently obtained promising results in a number of artificial intelligence issues, leading us to apply them to the challenge of recognizing citrus fruit and leaf diseases. In this approach, an integrated approach is used to suggest a convolutional neural networks (CNNs) model. The proposed CNN model is intended to differentiate healthy fruits and leaves from fruits/leaves with common citrus diseases such as black spot, canker and citrus blight. The proposed CNN model extracts complementary discriminative features by integrating multiple layers.
Keywords: Citrus leaf diseases, citrus fruit diseases detection, convolutional neural network and Deep Learning.

I. INTRODUCTION

Agrarian efficiency is something on which economy profoundly depends. This is the one of the reasons that disease recognition in plants assumes a significant job in agribusiness field, as having disease in plants are very characteristic. In the event that appropriate consideration isn't taken here, at that point it causes genuine impacts on plants and because of which individual item quality, amount or efficiency is influenced. Recognition of plant sickness through some auto-programmed strategy is useful as it diminishes a huge work of observing in huge ranches of crops, and at beginning period itself it identifies the side effects of sicknesses for example at the point when they show up on plant leaves. Innovation helps individuals in expanding the generation of food. Anyway the generation of food can be influenced by number of factor, for example, climatic change, infections, soil fruitfulness and so forth. Out of these, disease plays major job to influence the generation of food. Agriculture plays a significant job in Indian economy. Leaf spot infections debilitate trees and bushes by intruding on photosynthesis, the procedure by which plants make vitality that supports development and guard frameworks and impacts survival .

Fruit trees play an important role in any state's economic development. One of the most well- known fruit plant species is the citrus plant, which is high in vitamin C and widely used in the Indian sub-Continent, the Middle East and Africa. Citrus plants are associated with many health advantages, as well as being used as a raw material in the agricultural industry for the production of several types of other agri-products, including jams, sweets, ice cream, and confectionery, etc. Citrus, Pakistan's most important fruit crop, accounts for a significant portion of the country's horticultural exports.

Citrus fruit plants, on the other hand, are vulnerable to a wide range of infections, including black spots, cankers, citrus early blight and citrus late blight. The canker is highly contagious and is found in citrus trees and is mostly on the leaves or fruit. There are reports of crop losses of approximately 22% in Kinnow, 25-40% in sweet oranges, 15% in grease 10% in sweet limes and 2% in lemons, respectively. A large proportion of quality export fruit is refused every year due to signs of citrus fruit diseases. As a result, timely identification of citrus diseases has the potential to reduce losses and costs while also improving product quality. Deep learning, on the other hand, can learn the hierarchical features of pathologies automatically, eliminating the need to manually design the morphological operations of feature extraction and classifiers. The deep learning approach excels in several fields, including signal processing pedestrian detection, face recognition, road crack detection, biomedical image analysis, and many others.

We propose an integrated deep learning model for automated citrus fruit disease detection, based on the tremendous results of CNN-based methods in image classification.

A. Problem Statement

Human experts play a crucial role in these complex multi-step architectures. Crop illnesses are a significant danger to plants growth; however their fast recognizable proof stays troublesome in numerous pieces of the world due to the absence of the fundamental foundation. This problem is overcome by blend of expanding worldwide computer infiltration and ongoing advances in neural science made conceivable by profound learning has made ready for system helped disease finding and suggesting required. The proposed project is to detection of citrus fruit and leaves diseases using cnn.

B. Objectives

The aim of this work is to develop a deep convolutional neural network that learned features directly from the input of citrus fruit and leaves images and classifying the plant leaves and fruit into healthy or diseased and if it is a diseased , it will show corresponding disease name. Therefore objectives of proposed system are as follows:

1) To develop a deep convolutional neural network that can identify citrus fruit and leaf diseases and classify them into different classes.
2) To develop a network that learns from dataset and still demonstrates superior performance for Citrus fruit or leaves Diseases detection.
3) To develop an efficient approach to training a deep learning model with an balanced dataset.
4) To do the perform analysis of the proposed system for validation.

C. Proposed System

The aim of this project is to detection of citrus fruit and leaves diseases. The proposed method uses CNN model for classifying citrus fruit and leaf diseases into different classes, namely black spot, canker, early blight and late blight. The proposed deep learning model integrates a sufficient number of layers and parameters. The main purpose of proposed system is to detect the disease of citrus by using feature extraction methods where features such as shape, colour and texture are taken into consideration. The proposed approach is under implementation and is expected to give better accuracy as compared to conventional approaches.

II. LITERATURE SURVEY

In 2016, NoaSchor, Avital Bechar ,Time a Ignat present an automated location framework for joined recognition of two significant dangers of nursery ringer peppers: Powdery buildup (PM) and Tomato spotted wither infection (TSWV). The framework depends on a controller which encourages arriving at different location presents. A few identification calculations are created dependent on head part investigation (PCA) and the coefficient of variety (CV). Tests find out the framework can effectively identify the plant And arrive at the identification posture required for PM, yet it experiences issues in arriving at the TSWV discovery present.

In 2016,Lucas G. Nachtigall and Ricardo M. Araujo ponders the utilization of Convolutional Neural Systems to naturally distinguish and characterize sicknesses, wholesome insufficiencies and harm by herbicides on apple trees from pictures of their leaves. This errand is basic to ensure a high nature of the subsequent yields and is at present to a great extent performed by specialists in the field, which can seriously constrain scale and include to costs.

In 2016, Davoud Ashourloo, Ali Akbar Matkan planned for building up an unearthly malady file that can distinguish the phases of wheat leaf rust malady at different DS levels. To meet the point of the investigation, the reflectance spectra (350–2500 nm) of tainted leaves with various side effect parts and DS levels were estimated with a spectroradiometer.

In 2015, Aakansha Rastogi, Ritika Arora , Shanu Sharma proposed the framework which takes a shot at preprocessing, highlight extraction of leaf pictures from plant town dataset pursued by convolution neural system for grouping of ailment and suggesting Pesticides utilizing Tensor stream innovation. The principle two procedures that they use in our framework is android application with Java Web Services and Deep Learning. They have use Convolution Neural Network with various layers five, four and three to prepare our model and android application as a UI with JWS for association between these frameworks.

In 2014, Ms. Kiran R. Gavhale, Prof. UjwallaGawande,Mr. Kamal O.Hajari present about the picture handling methods utilized in performing early recognition of plant illnesses through leaf highlights assessment. The goal of this work is to actualize picture examination and characterization methods for extraction and characterization of leaf maladies. Leaf picture is caught and after that handled to decide the status of each plant.

In 2008, Santanu Phadikar and Jaya Sil depicts a product model framework for rice sickness recognition dependent on the tainted pictures of different rice plants. Pictures of the tainted rice plants are caught by advanced camera and prepared utilizing picture developing, picture division procedures to recognize contaminated pieces of the plants. At that point the tainted piece of the leaf has been utilized for the arrangement reason utilizing neuralsystem.

III. SYSTEM DESIGN

A. System Architecture

The system has been built using CNN algorithm which is a widely used technique in Deep learning. Deep learning refers to neural networks with a deep number of layers (usually more than five) that extract a hierarchy of features from raw input images. Deep learning extracts complex, high-level features from the images and trains a large amount of data, thus resulting in greater accuracy. Owing to significantly increased GPU processing power, deep learning methods allow us to train a vast amount of imaging data and increase accuracy despite variations in images.

CNN consists of layers of convolution, pooling, activation function, and fully connected layers with each layer performing specific functions. Input images are convolved across the kernel by the convolutional layer to produce feature maps. In the pooling layer, as the value transferred to the successive layer, the results obtained from preceding convolutional layers are down sampled using the maximum or average of the specified neighborhood. The most popular activation functions are the rectified linear unit (ReLU) and the leaky ReLU, which is a modification of ReLU. The ReLU transforms data nonlinearly by clipping off negative input values to zero and passing positive input values as output. The results of the last CNN layer are coupled to loss function to provide a forecast of the input data. Finally, network parameters are obtained by decreasing the loss function between prediction and ground truth labels along with regularization constraints. In addition, weights of the network are updated at each iteration using back-propagation until the convergence.

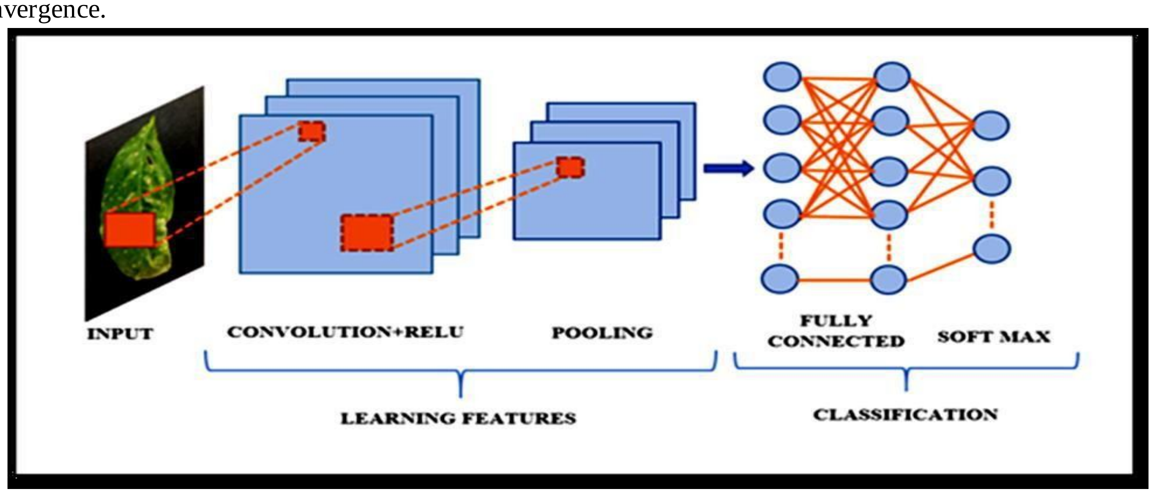

Fig. 1 Architecture of proposed Citrus fruit and leaves disease Prediction System

B. Dataflow Diagram

Figure 2 depicts DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.

Training phase: A set of citrus fruit and leaf disease images are pre-processed for feature extraction and segmentation. The training phase can be summarized as follows:

1) Extract features such as Texture, Shape and colour from the pre-processed data.
2) Train a CNN classifier using this feature set.

The output of the training phase is a trained classifier capable of predicting classification label based on features of different diseases of citrus.

The performance of the trained classifier can be evaluated using measures like training accuracy, testing accuracy and validation loss.

Classification: This phase can be summarized as follows:

- Take as input, from test data.
- Pre-process the test image.
- Extract the required features from the input.
- Use the trained classifier to predict the citrus test image results.

The output of this phase is classified citrus leaf or fruit as Normal or Abnormal. If it’s abnormal then particular disease name is specified.

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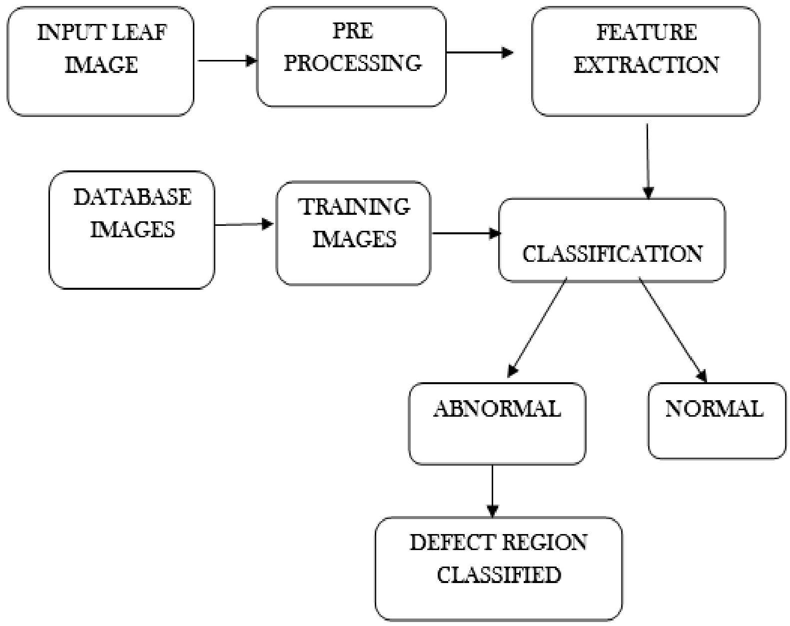

Fig. 2 Dataflow Diagram

C. Flow chart Diagram

The flow chart diagram shows a workflow or process. It is defined as a step by step approach solving task. The following are the some of the steps involved in proposed flowchart.

The input test image is acquired and preprocessed in the next stage and then it is converted into array form for comparison.

The selected database is properly segregated and preprocessed and then renamed into proper folders.

The model is properly trained using CNN and then classification takes place.

The comparison of the test image and the trained model take place followed by the display of the result.

If there is a defect or disease in the plant the software displays the disease.

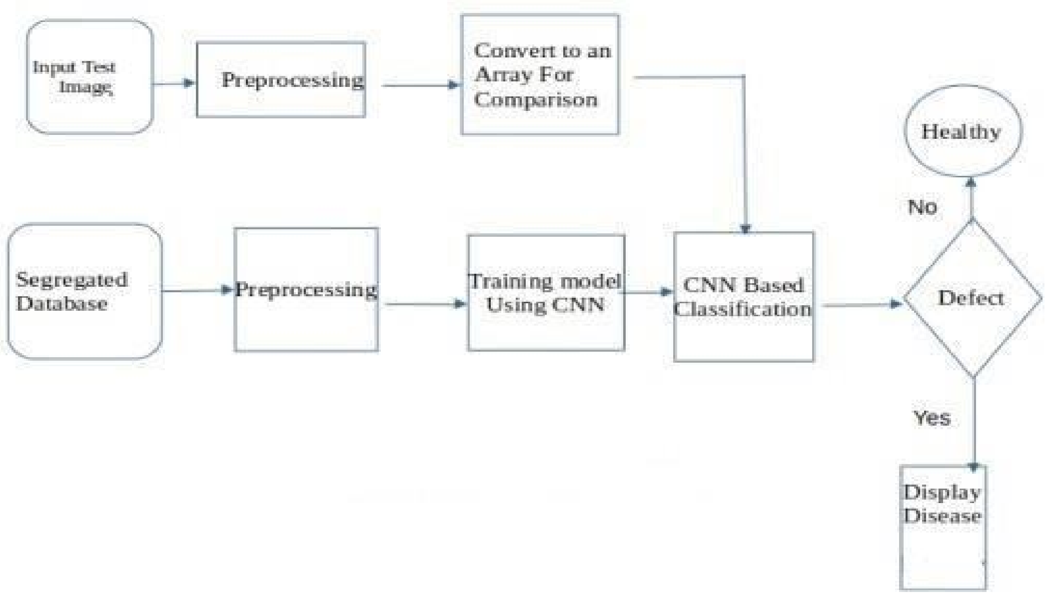

Fig. 3 Flow Chart Diagram

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IV. IMPLEMENTATION

1) *Dataset:* In the first module, we developed the system to get the input dataset for the training and testing purpose. The dataset consists of 5000+ images of citrus fruit and leaves diseases.
2) *Importing the Necessary Libraries:* We will be using Python language for this . First we will import the necessary libraries such as keras for building the main model, sklearn for splitting the training and test data, PIL for converting the images into array of numbers and other libraries such as pandas, numpy, matplotlib and tensorflow.
3) *Retrieving the Images:* We will retrieve the images and their labels. Then resize the images to (224,224) as all images should have same size for recognition. Then convert the images into numpy array.
4) *Splitting the Dataset:* Split the dataset into train and test. 80% train data and 20% test data.
5) *Convolutional Neural Networks*

The objectives behind the first module of the course 4 are:

- To understand the convolution operation
- To understand the pooling operation
- Remembering the vocabulary used in convolutional neural networks (padding, stride, filter, etc.)
- Building a convolutional neural network for multi-class classification in images

6) *Building the Model:* For building the model we will use sequential model from keras library. Then we will add the layers to make convolutional neural network. In the first 2 Conv2D layers we have used 32 filters and the kernel size is (5,5).

The below figure is a complete flow of CNN to process an input image and classifies diseases based on AlexNet Architecture.

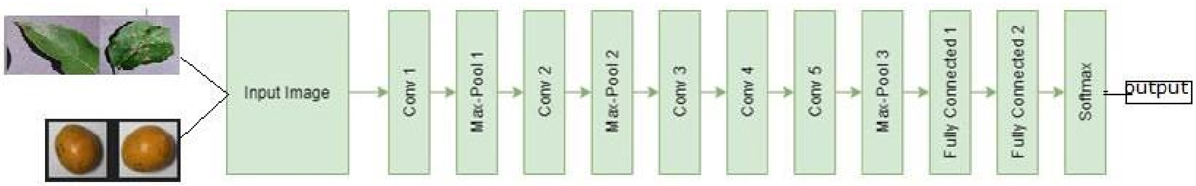

Fig 4: CNN AlexNet Architecture

Alex Krizhevsky is the creator of the AlexNet platform, a state-of-the-art pre- trained CNN. It has used for numerous comparisons in several different fields. It is a deep CNN which is consists of eight layers including one input layer, five convolution layers followed by three maxpooling, seven ReLU layers, two fully connected layers, one SoftMax layer, and finally one output layer. AlexNet could be a leading architecture for any object-detection task and will have huge applications within the computer vision sector of computer science problems. within the future, AlexNet could also be adopted over CNNs for image tasks. The input to the present model is that the images of size 227X227X3.

In AlexNet's first layer, the convolution window shape is 11×11 with 96 filters and stride 4.the activation function employed in this layer is ReLU. The ReLU activation function makes model training easier when using different parameter initialization methods. The output feature map is 55X55X96. Consequently, a bigger convolution window is required to capture the article. The convolution window shape within the second layer is reduced to 5×5, followed by 3×3. Additionally, after the primary, second, and fifth convolutional layers, the network adds max-pooling layers with a window shape of 3×3 and a stride of two.

The number of filters is increasing as going deeper in architecture and extracting more features from images. Also , the filter size is reducing ,which means initial filter was larger and as go head the filter size is decreasing ,resulting during a decrease within the feature map shape. The flattening is utilized to convert multidimensional array from pooled feature maps into single continuous linear vector. Flattened matrix is fed as input to the fully connected layer to classify the image. After the last convolutional layer there are two fully connected layers with 4096 outputs. AlexNet controls the model complexity of the fully connected layer by dropout. Finally, we've got the last fully connected layer or output layer with 5 neurons as we've 5 classes within the data set. The activation function used at this layer is Softmax.

- *Apply the Model and Plot the graphs for Accuracy and Loss:* We will compile the model and apply it using fit function. Then we will plot the graphs for accuracy and loss. We go training accuracy of fruit and leaves diseases is above 85% and validation accuracy is above 90% on the test data that detects diseases accurately.
- *Accuracy On Test Set:* We got a accuracy of 92% on test data of citrus leaves and 86 % on test data of citrus fruit diseases.

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V. RESULTS AND SCREENSHOTS

The figure 5 depicts the output screen of the proposed system. It is the home page in which we have Train Classifier button to training the model with new datasets. Also we have provided choosing button to picking images for testing. Once we choose the image by clicking predict button it will predict the uploaded image results. We use django framework for fron-end. Once we start the django server we get this page in our local host port.

Fig. 5: Home Page of proposed system

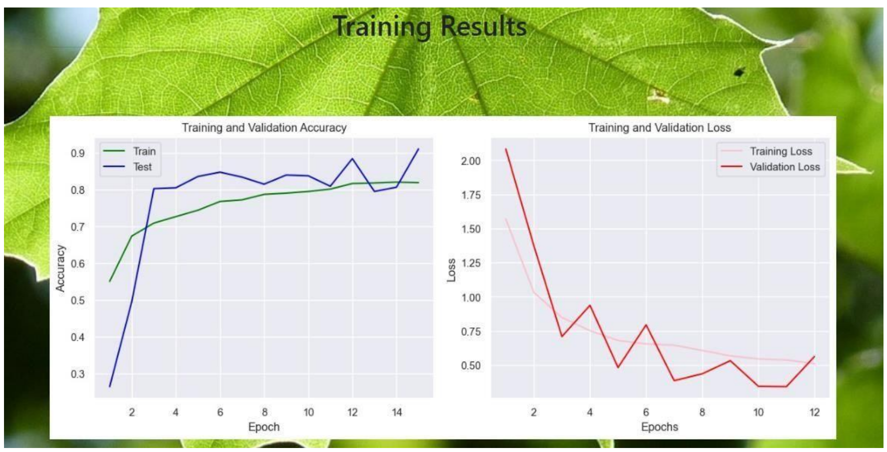

Fig 6: Results of Training model

Figure 6 shows the model training and testing accuracy and loss in the two different graphs respectively. We can also see that left graph shows that model has not yet over-learned the training dataset, showing comparable skill on both datasets. The right graph shows that the plot of loss, we can see that the model has comparable performance on both train and validation datasets (labeled test).

Fig. 7a: Predicted result of the test data image.

Fig. 7b: Predicted result of the test data image.

Fig. 7c: Predicted result of the test data image.

Fig. 7d: Predicted result of the test data image.

Figure 7(a-d) shows the results of test image predicted. Results contain the details of disease identified. Four Citrus leaves diseases are identified such as canker , blacterial spot, early_blight and late_blight.

Fig 8: Home page of Citrus Fruit disease identification system.

The fig shows home page of the citrus fruit disease identification system. Here, we have Train Classifier button to train the citrus fruits using CNN model. Also we have provided choose button to selecting images for testing, once choosing image and then click predict button.

Fig 9: Training Results of Citrus fruits Recognition system

This above fig shows overall training and testing accuracy of citrus fruit disease classification and also training and validation loss of the system. The testing accuracy of citrus fruit disease classification is above 85%.

Fig 10a: Predicted Citrus disease is Black-spot

Fig 10b: Predicted Citrus disease is Citrus-Canker

VI. CONCLUSION

In this Work, the basic Convolutional Neural Network (CNN) architecture model has been used to classify Citrus fruit and leaf diseases. Convolutional Neural Network (CNN) architecture model is used to avoid the expensive training from scratch and to get higher efficiency with limited number of datasets. The proposed work was able to give a good accuracy where training accuracy is above 90% and validation accuracy is 86% on the test data with very small misclassifications on normal and very mild demented. Multiple plant disease datasets of varying sizes may be used to improve the model's performance.

In future the accuracy and the speed can be increased by use of GooglesGPU for processing.

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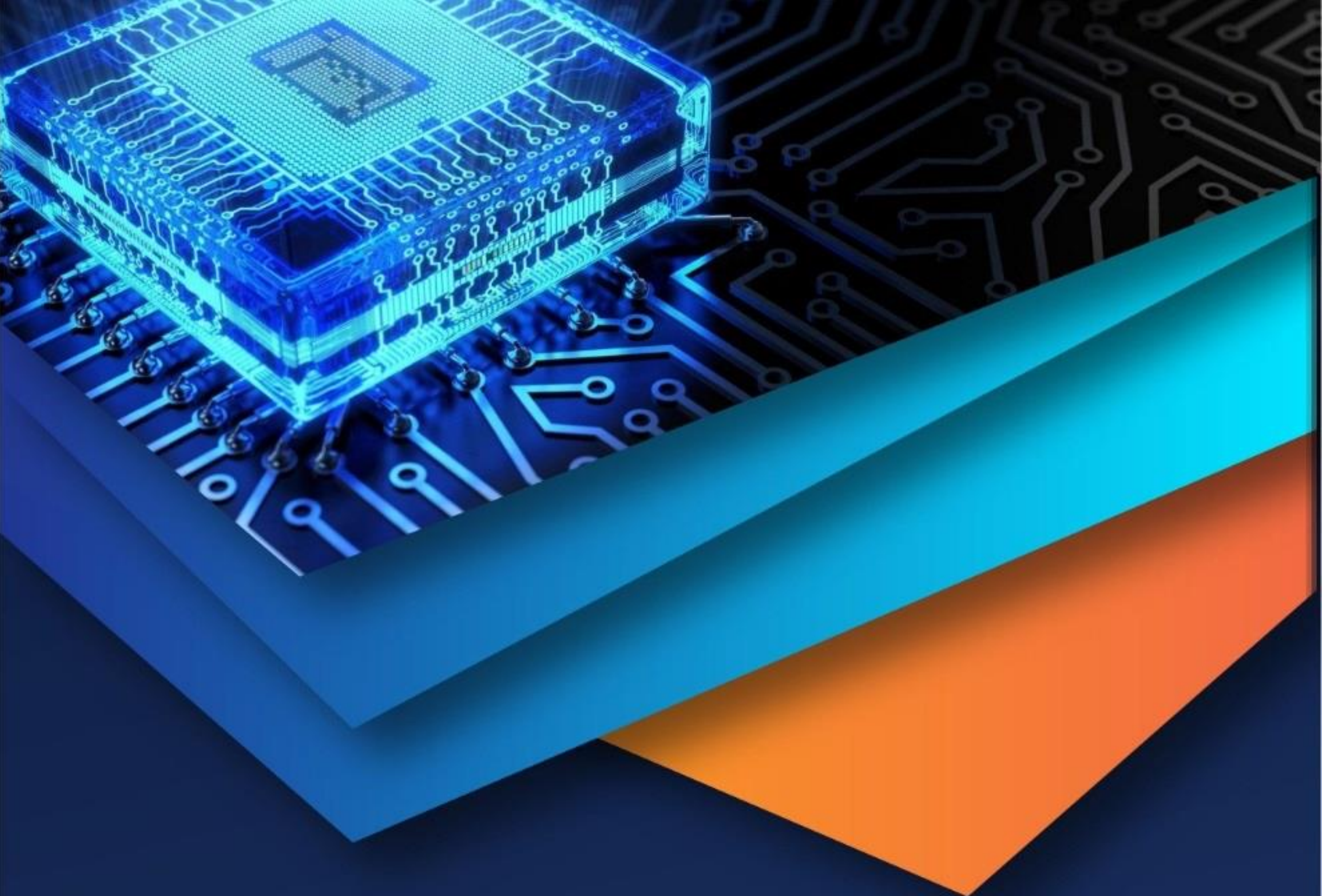

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