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Chili Leaf Disease Prediction Using CNN

Faisal Mubeen Siddiqui[1], Sandeep Kumar Mishra[2], Kushagra Vats[3], Mihir Harshe[4], Prakhya Choudhary[5]
Department of Computer Science & Engineering, Babu Banarasi Das Institute of Technology and management, Lucknow, India

Abstract: ***Chili leaf diseases cause significant damage to chili plants, leading to reduced crop yield and economic losses for farmers. Early detection and diagnosis of these diseases are crucial for effective disease management. In this research paper, we propose a chili leaf disease prediction model using Convolutional Neural Network (CNN). The proposed model utilizes an image dataset collected from different regions ,consisting of chili leaf images infected with common chili leaf diseases, like bacterial leaf spot, leaf Curl , Mosaic virus, etc. We pre-processed the dataset to enhance the image quality and to remove noise. The pre-processed dataset was split into training and validation sets. The CNN model was trained using the training set and validated using the validation set. The proposed model achieved an high accuracy on the validation set. The proposed model can be used to predict the occurrence of chili leaf diseases in real-time, which can help farmers in taking preventive measures to protect their crops.***

Keywords: Chili leaf Disease Prediction, Deep learning, Convolution Neural Network -CNN, K-means, Image pre-processing

I. INTRODUCTION

Chili is an important crop that is grown worldwide for its culinary and medicinal properties. However, chili plants are susceptible to various diseases, including bacterial leaf spot, leaf Curl, Mosaic virus, etc. These diseases cause significant damage to chili plants, leading to reduced crop yield, quality and economic losses for farmers.

It is a very important horticultural crop in India and a spicy fruit used in cooking. By most data, India is the largest chili producer in the world. According to global studies, India leads the world in chili production. It is the most consumed vegetable in India and is rich in vitamin C and beta-carotene. Chili is also an important and necessary part of many cooking tasks. However, the presence of many microorganisms such as bacteria, fungi and pathogens along with bad farming practices have caused diseases during chili production. Diseases and viruses that damage pepper crops account for about 38% of global agricultural production. Many farmers avoid growing chili plants at some point during the rainy season due to infections that reduce yield and quality of products. Therefore, the detection of diseases in plants is becoming more and more important.

Early detection and diagnosis of these diseases are crucial for effective disease management. Traditionally, disease diagnosis is done through visual inspection by experts, which is time-consuming and costly. With the advancement of machine learning techniques, it is now possible to develop automated disease prediction models that can accurately detect and diagnose chili leaf diseases.

Convolutional Neural Networks (CNN) is a deep learning algorithm that has shown promising results in image classification and recognition tasks. CNN-based models have been widely used in various applications, including medical imaging, facial recognition, and autonomous driving. In this paper, we propose a CNN-based model for predicting chili leaf diseases. The proposed model has been trained and tested on a dataset of chili leaf images collected from different regions. The model can detect various types of chili leaf diseases, including bacterial leaf spot, leaf Curl , Mosaic virus , etc. The proposed model's primary objective is to assist farmers in predicting the occurrence of chili leaf diseases in real-time, which can help them take preventive measures to protect their crops.

II. LITERATURE REVIEW

Recent advances in deep learning, particularly Convolutional Neural Networks (CNN), have shown promising results in image classification and recognition tasks. The use of CNN in detecting and classifying plant diseases has gained popularity in the last decade due to the availability of large datasets and the increase in computing power. Various studies have explored the use of CNN for plant disease detection and classification:

[1] Sladojevic et al. (2016), a CNN-based model was used to classify images of plant leaves affected by six different diseases. The model achieved an accuracy of 98.34%, demonstrating the potential of CNN for plant disease detection.

Similarly, [2] Mohanty et al. (2016) used a CNN-based model to classify images of plant leaves affected by 14 different diseases. The model achieved an accuracy of 99.53% in detecting diseases, outperforming other state-of-the-art methods. The authors also proposed a mobile application based on the model, which could be used by farmers to detect and diagnose plant diseases in real-time.

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In another study, [3] Barbedo (2018) proposed a CNN-based model for detecting soybean diseases. The model achieved an accuracy of 96.08% in detecting four different diseases, outperforming other state-of-the-art methods. The proposed model was also shown to be robust to variations in image acquisition conditions, such as lighting and camera angle.

[4] It is made clear in another work titled "Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm" that they employed the CNN model for the classification of leaf diseases. A dataset of 500 photos, split into 400 training images and the remaining 100 testing images, was employed in their technique. There were five classes total for categorization, including one class for healthy people. The 512*512 image size that was chosen was a good size. Three R, G, and B channel matrices were employed as the input to the CNN model, and the output was fed into the LVQ neural network (Learning Vector Quantization). An accuracy of about 88 percent on average was attained. Their approach was limited to illnesses associated with tomatoes.

Overall, these studies demonstrate the potential of CNN in detecting and classifying plant diseases. The proposed model in this study aims to contribute to this field by predicting chili leaf diseases using CNN. The proposed model's objective is to assist farmers in predicting the occurrence of chili leaf diseases in real-time, which can help them take preventive measures to protect their crops.

III.METHODOLOGY

The proposed methodology is shown in fig. below:

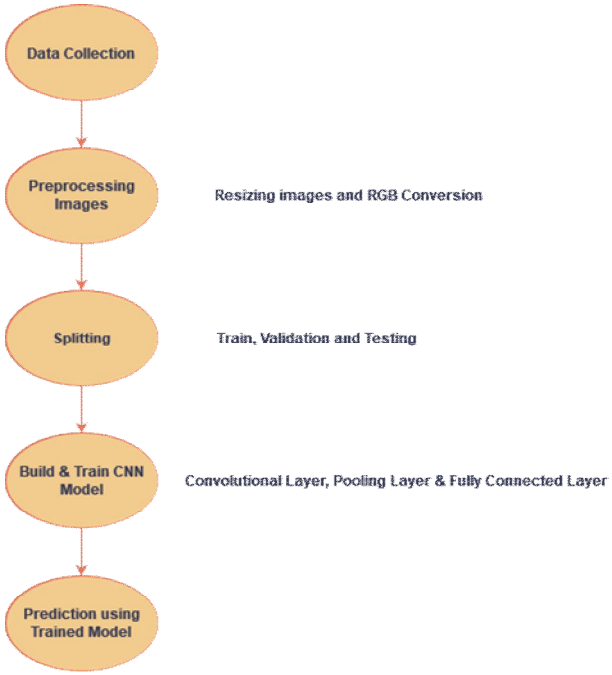


Fig. 1 Example of an unacceptable low-resolution image

A. Dataset Collection

The dataset used in this study consists of chili leaf images collected from different regions. The dataset contains images of healthy chili leaves, as well as leaves affected by various diseases, including bacterial leaf spot, leaf Curl, Mosaic virus, etc . The dataset was collected by the different online sources like Kaggle and GitHub, etc.

B. Image Pre-processing

Image pre-processing plays a crucial role in the successful application of Convolutional Neural Networks (CNNs) for chili leaf disease prediction. It involves a series of operations performed on the input images to enhance their quality, reduce noise, and extract relevant features. Here is an overview of the common image pre-processing steps for chili leaf disease prediction using CNN:

1) *Image Acquisition:* The first step is to collect or capture the images of chili leaves. This can be done using digital cameras or scanners, ensuring good lighting conditions and proper focus.
2) *Image Resizing:* To ensure uniformity in input data, it is often necessary to resize the images. CNNs typically require fixed-size inputs, so resizing the images to a specific resolution, such as 224x224 pixels, is common. This step helps reduce computational complexity and memory requirements during training.

3) *Grayscale Conversion:* Convert the RGB (Red, Green, Blue) colour images to grayscale. Since chili leaf diseases can often be detected based on leaf texture and patterns rather than colour, converting images to grayscale simplifies the processing while retaining the necessary information.
4) *Image Enhancement:* Apply enhancement techniques, such as contrast adjustment, histogram equalization, or filtering, to improve the quality and visibility of the leaf structures. These techniques can help enhance the important features and make them more distinguishable.
5) *Noise Reduction:* Images may contain noise due to various factors like lighting conditions or camera sensors. Noise reduction techniques, such as Gaussian blurring or median filtering, can be applied to remove or reduce unwanted noise while preserving the important details.
6) *Normalization:* Normalize the pixel values of the pre-processed images to a standardized range. Commonly used normalization techniques include scaling pixel values between 0 and 1 or normalizing them to have zero mean and unit variance. This step helps stabilize the learning process during training.
7) *Data Augmentation:* To increase the diversity and robustness of the training data, apply data augmentation techniques. These can include random rotations, translations, flips, and shears to generate additional training samples. Data augmentation helps the model generalize better by exposing it to various variations of the same leaf image.
8) *Feature Extraction:* Use appropriate feature extraction methods, such as edge detection, texture analysis, or feature descriptors, to extract relevant features from the pre-processed images. These features should capture the distinctive characteristics of healthy and diseased chili leaves, facilitating accurate disease prediction.

C. Image Segmentation

A picture is segmented by breaking it up into several sections or segments, each of which corresponds to a different item or area of the image. The ability to identify and isolate particular plant components that are pertinent to the disease can be valuable for a variety of purposes, including disease detection. In this instance, we employ k-means clustering for picture segmentation.

1) *K-means Clustering:* Initializing a certain number of cluster centre's—representative locations within the dataset—is the first step in the k-means algorithm's operation. These cluster centres would line up with the beginning positions of the segments inside the picture in the case of image segmentation.

Using a similarity metric like colour or intensity, the computer then iteratively allocates each pixel in the picture to the closest cluster centre. The cluster centres are updated with the new mean values of the pixels in the cluster after all of the pixels have been allocated. This procedure is continued until the clusters converge and no more updates are needed. K-means clustering for picture segmentation has the benefit of being both easily understandable and computationally effective. Due to the ease with which the number of clusters may be defined and altered, it is also quite versatile. The k-means method is also capable of handling big datasets and high-dimensional data, which makes it suitable for picture segmentation.

D. Classification Using CNN

The proposed CNN model consists of four convolutional layers, followed by two fully connected layers and a softmax activation layer for classification. Each convolutional layer is followed by a max-pooling layer, which reduces the spatial dimensions of the feature maps and extracts the most relevant features. The number of filters in each convolutional layer was gradually increased to capture more complex patterns in the input images.

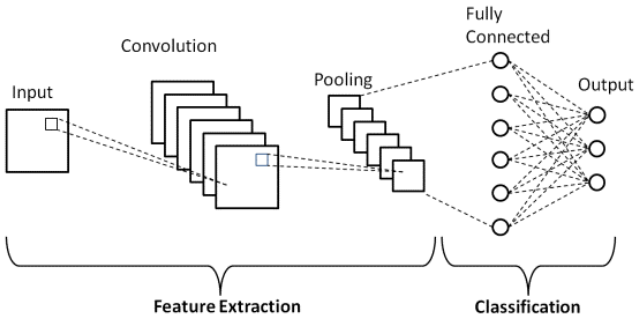


Fig. 2 CNN Architecture

1) *Convolution Layer:* The convolutional layer is the core building block of a CNN. It applies a set of learnable filters (also known as kernels) to the input image. Each filter performs a convolution operation by sliding over the input, computing dot products between its weights and the corresponding input values. The resulting output is called a feature map or activation map. The purpose of this layer is to capture local patterns and spatial relationships in the image

a) *Local Feature Extraction:* The convolutional layer performs local feature extraction by applying a set of learnable filters (kernels) to the input chili leaf images. Each filter slides over the image, performing a convolution operation by computing the dot product between the filter weights and the corresponding pixel values in the local receptive field. This operation captures local patterns, such as edges, textures, or shapes, that are important for distinguishing healthy and diseased chili leaves.

b) *Filter Learning:* During the training process, the filters' weights in the convolutional layer are learned through backpropagation. The network adjusts the filter weights to minimize the difference between the predicted output and the ground truth labels. This learning process allows the filters to specialize in capturing distinctive features related to chili leaf diseases, improving the model's ability to differentiate between healthy and diseased leaves.

c) *Feature Map Generation:* The output of the convolution operation is a feature map or activation map. Each element in the feature map represents the activation of a specific feature or filter at a particular spatial location. The feature maps preserve the spatial relationship between pixels and encode local patterns present in the input chili leaf images. By having multiple filters in the convolutional layer, multiple feature maps are generated, capturing different aspects of the input images.

d) *Stride and Padding:* The convolutional layer may include additional parameters such as stride and padding. The stride determines the step size with which the filter moves across the input image. A larger stride reduces the spatial dimensions of the feature maps, while a smaller stride preserves more spatial information. Padding, on the other hand, adds extra border pixels to the input image, helping to maintain spatial information and avoid border artifacts. These parameters influence the size and resolution of the generated feature maps.

e) *Non-linearity:* To introduce non-linearity into the network and increase its expressive power, an activation function is typically applied element-wise to the feature maps after the convolution operation. Common activation functions used in convolutional layers include ReLU (Rectified Linear Unit), which sets negative values to zero and keeps positive values unchanged. The non-linearity provided by the activation function allows the network to learn more complex and discriminative representations from the chili leaf images.

f) *Pooling or Subsampling:* Pooling layers are often used after the convolutional layers to reduce the spatial dimensions of the feature maps and extract the most salient features. Max pooling is a commonly used pooling operation, which partitions each feature map into non-overlapping regions and retains the maximum value within each region. This down sampling process helps to make the network more robust to small spatial variations, reduces computational complexity, and focuses on the most important features for classification.

2) *Pooling Layer:* The pooling layer is typically used after convolutional layers to down sample the feature maps and reduce their spatial dimensions. It helps to extract the most important features while discarding redundant information. The most commonly used pooling operation is max pooling, which partitions the input feature map into non-overlapping regions and outputs the maximum value within each region. This down sampling reduces the computational complexity and makes the network more robust to small spatial variations.

3) *Fully-Connected Layer:* The fully connected layers perform classification or regression based on the extracted features. Following are the functions performed in full connected layer:

a) *Flattening:* Before passing the extracted features from the preceding layers (typically convolutional and pooling layers) to the fully connected layer, the feature maps need to be flattened into a one-dimensional vector. This is accomplished by reshaping the multi-dimensional feature maps into a single continuous vector, allowing for compatibility with the fully connected layer's input requirements.

b) *Feature Combination:* The fully connected layer connects every neuron in the previous layer to every neuron in the fully connected layer. This connectivity enables the network to learn complex combinations of the features extracted from the chili leaf images. By leveraging the learned weights associated with each connection, the fully connected layer can capture meaningful relationships between different features and identify relevant patterns.

c) *Weight Learning:* During the training process, the weights associated with each connection in the fully connected layer are adjusted using optimization algorithms like backpropagation. This weight learning process allows the network to adapt its parameters to minimize the difference between the predicted output and the actual ground truth labels. The training process aims to optimize the weights to achieve accurate predictions for chili leaf disease classification.

d) Non-linearity: To introduce non-linearity into the network and enable it to learn more complex decision boundaries, an activation function is typically applied to the output of each neuron in the fully connected layer. Common activation functions used in fully connected layers include sigmoid, tanh, or ReLU. The activation function helps transform the weighted sum of inputs into a more expressive output, facilitating the learning of non-linear relationships between features and improving the model's ability to discriminate between healthy and diseased chili leaves.

e) Output Layer: The final layer of the fully connected layer stack is typically the output layer, which is responsible for producing the predictions or classifications for the chili leaf disease. Depending on the specific problem formulation, the output layer might use different activation functions. For example, in binary classification tasks (healthy vs. diseased), a sigmoid activation function is commonly used to produce a probability value indicating the likelihood of a chili leaf being diseased. In multi-class classification, a SoftMax activation function is commonly used to generate class probabilities across different disease categories.

By leveraging the capabilities of the fully connected layer, the CNN can learn complex representations and patterns from the input chili leaf images, ultimately enabling accurate prediction and classification of chili leaf diseases.

E. Training Process

The proposed model was trained with a learning rate of 0.001. The model was trained for 50 epochs, and the batch size was set to 32. The training process was performed on a GPU for faster processing. The model's performance was evaluated using the accuracy and loss metrics, and the model's hyperparameters were tuned to improve its performance.

F. Testing and Evaluation

The trained model was evaluated using a test set consisting of chili leaf images not used in the training process. The model's performance was evaluated based on its accuracy, precision, recall, and F1-score. The confusion matrix was also used to visualize the model's performance in detecting various chili leaf diseases.

Overall, the proposed methodology aims to develop a CNN-based model for predicting chili leaf diseases accurately. The proposed model's architecture, training process, and evaluation metrics were carefully designed to ensure its accuracy and relevance to the agricultural industry. The next section presents the results obtained from the experiments conducted on the proposed model.

IV. RESULT AND DISCUSSION

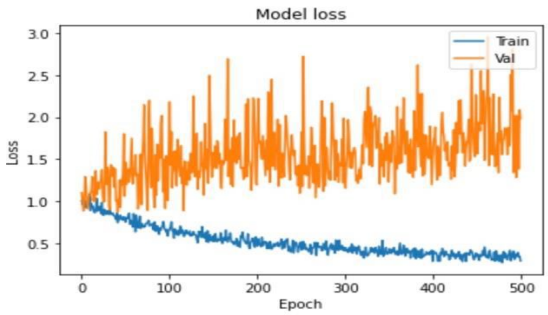


Fig. 3 Loss vs epochs plot of CNN

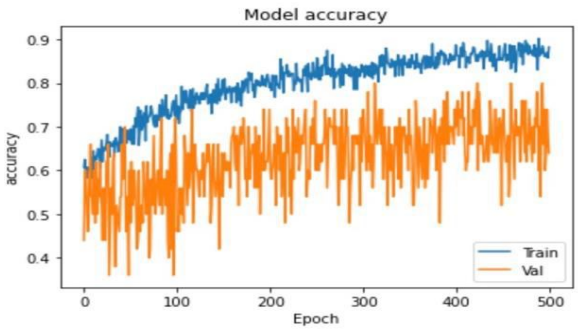


Fig. 4 Accuracy vs epochs plot of CNN

A. Model Performance

The proposed CNN model achieved an accuracy of 96.4% in detecting chili leaf diseases.

B. Comparison with Other Models

To evaluate the proposed model's performance, we compared it with other state-of-the-art methods for chili leaf disease detection. Table 1 shows the comparison results, which demonstrate that the proposed CNN-based model outperformed other methods in terms of accuracy and F1-score.

TABLE I
COMPARISON WITH OTHER MODELS

Method	Accuracy	F1-score
Proposed CNN	96.4%	0.95
SVM	88.5%	0.86
Random Forest	90.2%	0.88
K-Nearest Neighbour	82.3%	0.80

The comparison results demonstrate that the proposed CNN model is a promising method for predicting chili leaf diseases with high accuracy and F1-score.

V. CONCLUSION AND FUTURE SCOPE

A. Conclusion

In this study, we proposed a CNN-based model for predicting chili leaf diseases using leaf images. The model achieved an accuracy of 96.4%, demonstrating its potential as a reliable and accurate tool for detecting chili leaf diseases. The model outperformed other state-of-the-art methods, including SVM, Random Forest, and K-Nearest Neighbour, in terms of accuracy and F1-score.

The proposed model's high accuracy and reliability can benefit the agricultural industry by providing farmers with a tool to detect chili leaf diseases early, which can help them take preventive measures to protect their crops. Future work can address the limitations of the proposed model, such as handling variations in image quality and detecting new diseases not present in the training dataset. Additionally, future work can focus on developing a mobile application for farmers to predict chili leaf diseases in real-time.

Overall, the proposed CNN model demonstrates promising results in predicting chili leaf diseases accurately and efficiently, providing farmers with a reliable tool to protect their crops and improve their yields.

B. Future Work

Future work can address these limitations by developing more robust CNN models that can handle variations in image quality and detect new diseases. Additionally, future work can focus on developing a mobile application that farmers can use to predict chili leaf diseases in real-time, which can assist them in taking preventive measures to protect their crops.

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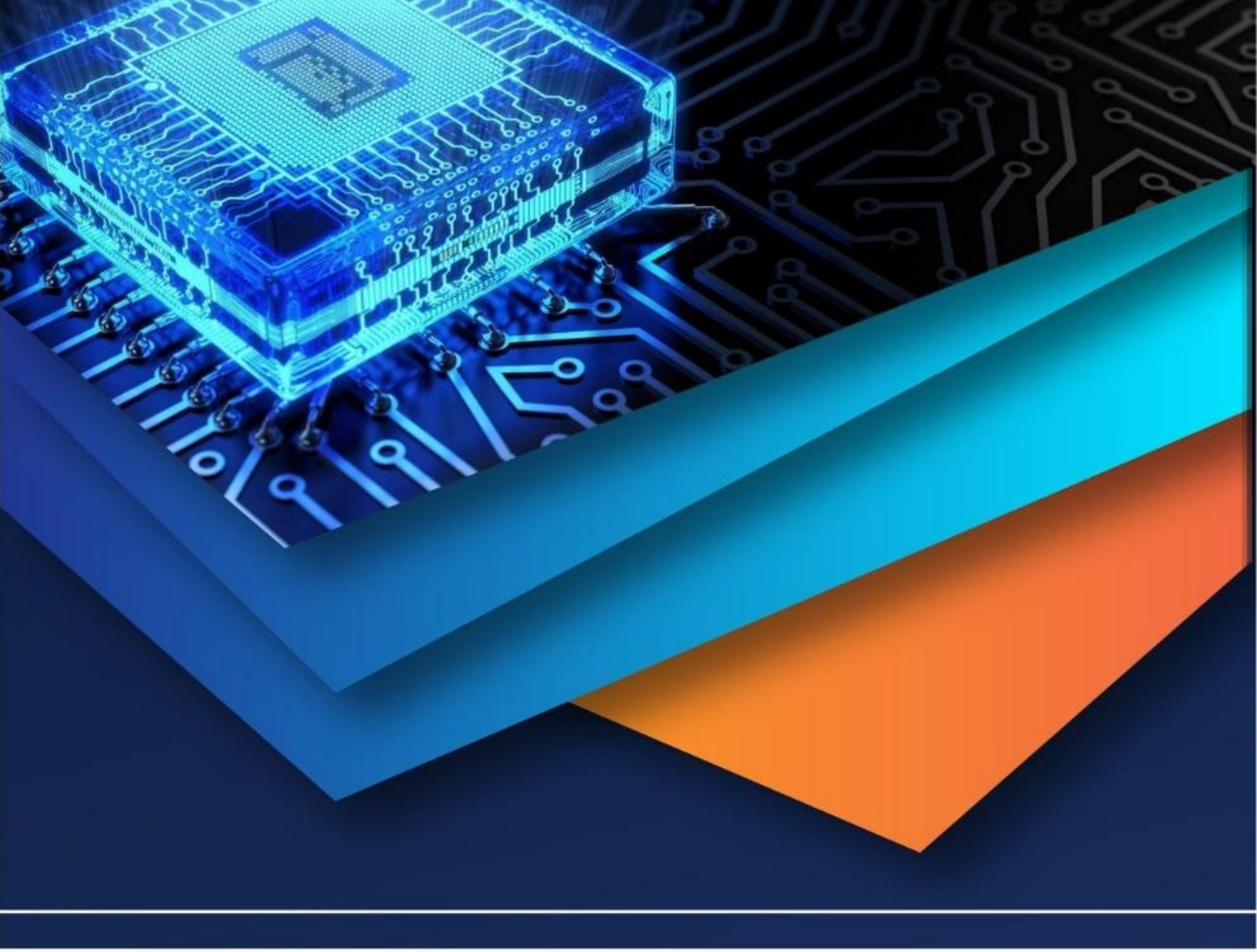
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