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A Survey Number-Based Deep Learning Framework for Automatic Crop Type Identification Using Satellite Imagery

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Abstract*: Correct crop identification is vital in agriculture for planning, when dealing with loans and for state oversight. Frequently, the particulars of crops are checked via inspection done by hand, which is slow and can be inaccurate. This study details a crop classification system which employs satellite pictures and deep learning models. A dataset – made up of satellite pictures taken from Google Earth, with one hundred pictures of rice, wheat, sugarcane, coconut and land with no plants – was labelled. In MATLAB, this dataset was put through training using transfer learning, and pre-set models like ResNet50, ResNet101, mobileNetv2, SqueezeNet, GoogleNet, inceptionV3, Resnet18.The models' performance was assessed by means of classification accuracy, and analysis of a confusion matrix. A straightforward land database was additionally constructed to link survey numbers to the satellite picture, and the crop type that was forecast. The findings demonstrate that deep learning is able to categorise crops well, from satellite pictures; and the system could be made better by enlarging the dataset and making use of data from several seasons.
Keywords: Crop detection, Transfer learning, Survey Number, Satellite Imagery, Agriculture.

I. INTRODUCTION

Agriculture is considered one of the major domains that support food production. For effective planning, it is also necessary to identify the type of crop grown in each area of land. Crop information can help government departments, banks, insurance companies, and many more. For effective crop information, proper crop monitoring techniques are required. Traditionally, identification of crops involves inspecting the crop's field or checking a farmer's records. This involves physically visiting these places and manually inspecting. This process may be cumbersome, especially with an increase in the number of agricultural lands. A system is required that can efficiently identify crops. Satellite images give us an opportunity to view agricultural areas without actually going there. Satellite images carry useful information on the respective land use and vegetation cover. However, it is not possible to process satellite images on our own to get relevant results, as there are large agricultural areas to be covered. This is where machine learning and deep learning techniques become helpful. Image classification techniques, particularly CNN, can be helpful to classify images into different classes.

There are many studies in which deep learning approaches have been used for crop classification. A good accuracy level has been reported in those studies; however, in some studies, large public databases are used, or the proposed approach is not focused on connecting crop classification results with land survey numbers. A more realistic approach is required. In this study, a crop classification system is proposed using a set of satellite images retrieved from Google Earth. A labeled dataset of certain crop types is trained using deep neural networks and transfer learning from the CNN model. Besides, a simple database structure of land is also designed to link the survey number with the satellite image and crop type. In summary, the main aim of the current study is to investigate the possibility of using deep learning methods to assist crop identification in an organized and useful manner.

II. RELATED WORK

Up to date developments in deep learning have greatly enhanced land cover and crop type classification based on remote sensing data, proving that convolutional neural networks when applied to multisource satellite data, such as Landsat and Sentinel data, are more accurate at agricultural mapping than conventional machine learning models. [2] A comparative study of deep learning, traditional machine learning algorithms, and Google Earth Engine regarding a crop classification task revealed that deep learning models have better performance and otherwise greater generalization ability on multispectral satellite image processing.

According to [3], a review of the deep learning models in multispectral remote sensing in land use and crop classification revealed that neural networks are capable of capturing spatial as well as spectral features, which results to better discrimination of vegetation classes, and higher classification accuracy. Convolutional and recurrent neural networks were integrated as a framework with multi-temporal Sentinel-2 data and red-edge vegetation indices with significant enhancement of crop mapping results through introduction of the temporal information during growing seasons. [5] An innovative crop-like classification method based on multitemporal remote sensing data and phenological data was used to strengthen the separation of crops having close spectral features through analysis of seasonal reflectance progress. A semantic segmentation model based on the U-Net architecture to identify crop types in satellite images enhanced spatial accuracy and precise delineation of the boundaries of crops as opposed to more traditional region-based classification methods. A classification fine crop model that utilizes the multitemporal Sentinel-2 imagery underlines the role of temporal feature to differentiate crops possessing similar spectral characteristics and enhance overall classification accuracy. The huge-scale review of satellite remote sensing based crop cover classification in Europe demonstrated the effect of various methodological techniques on the accuracy of the classification and also gave a clue on the ways to optimize the crop mapping strategies.

III.METHODOLOGY

A. System Architecture

The proposed system has four main modules, viz., user input, crop classification, database verification, and result generation.

First, the user enters the survey number and uploads the corresponding satellite image. To get the crop details, the survey number is used to fetch the registered crop details from the database.

The uploaded satellite image is processed and provided as input to the trained ResNet-101 which analyzes the image and predicts the crop type. Finally, after prediction, the system checks whether the predicted crop label matches the crop information present for the given survey number in the database. If both match, it shows "Pass". If they do not match, it shows "Fake". This architecture will enable crop claims to be verified in a straightforward and structured fashion.

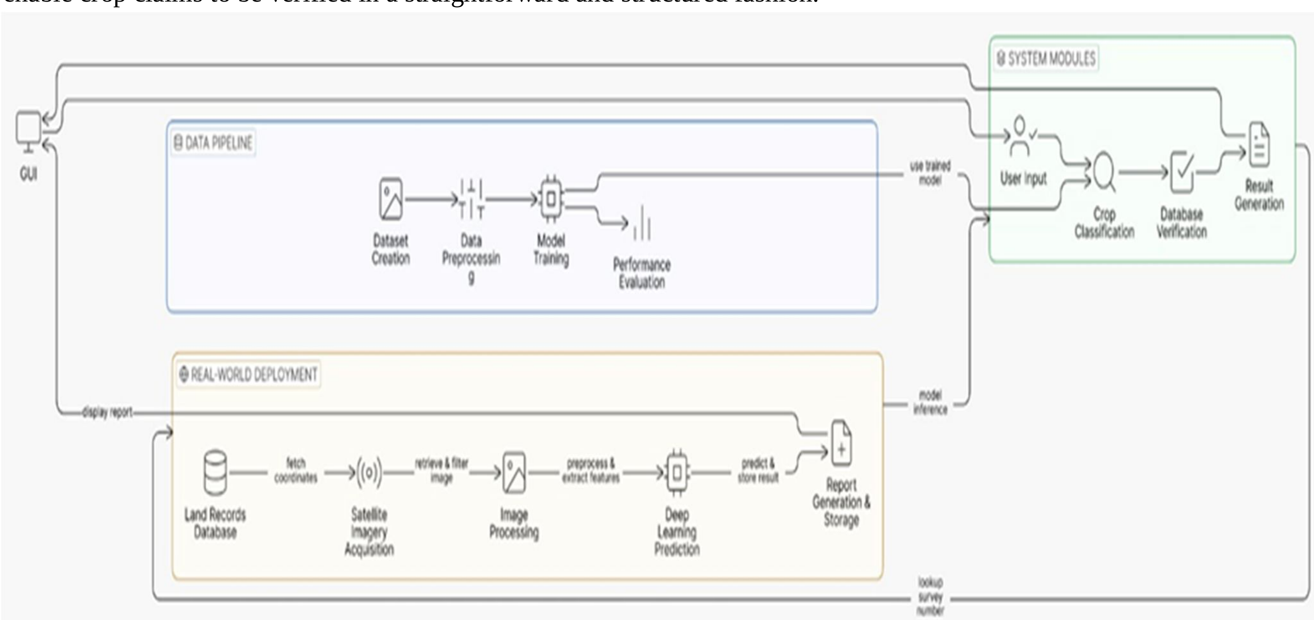
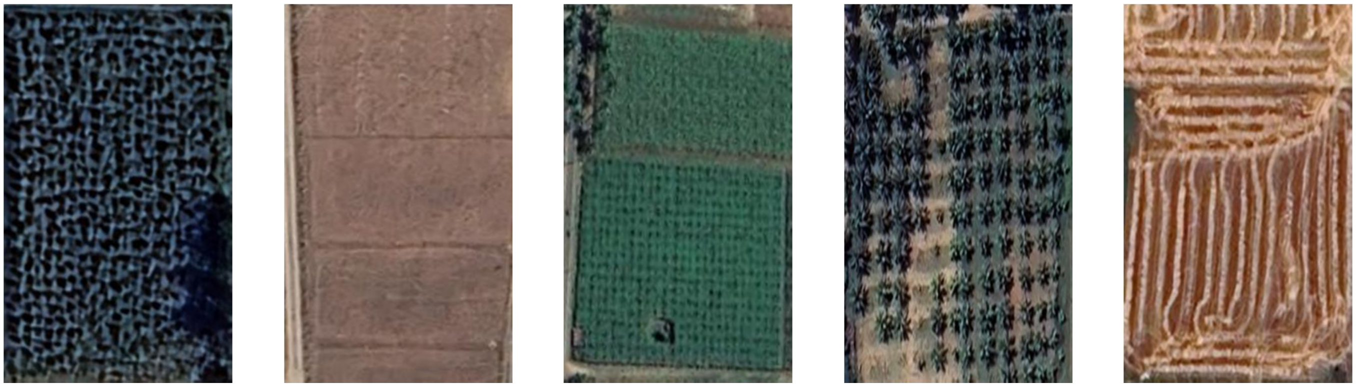


Fig. 1 Proposed System Architecture

B. Data Acquisition and Pre-processing

For this, since a proper public dataset is not available, a database for crop images needs to be created. Satellite images for five classes, i.e., rice, wheat, sugarcane, coconut, and barren land, have been collected from Google Earth. For each class, around 100 images have been obtained. Images are saved in separate folders, which can be used for automated labeling. All pictures were resized to match the size required by the pretrained CNN layer, such as 224x224 pixels. Low-quality images were removed, and pixels were normalized. The dataset was split into a training set and a validation set, which will be used for model performance evaluation.



(a) sugarcane (b) barren land (c) rice (d) coconut (e) wheat

Fig. 2 Dataset Images

C. Model Training and Evaluation

Transfer learning is applied using the pre-trained convolutional neural networks ResNet50, ResNet101, ResNet18, MobileNetV2, InceptionV3, GoogleNet and SqueezeNet. The last layer of these networks is replaced to match the number of crop classes. Finally, fine-tuning is performed using the MATLAB Deep Learning Toolbox with selected hyperparameters.

D. Performance Evaluation

The performance of the proposed crop detection system is assessed using the standard classification metrics, as derived from the confusion matrix. Let TP (True Positive) stand for the correct classification of crop regions, TN (True Negative) stand for the correct classification of non-crop regions, FP (False Positive) stand for misclassified non-crop regions as crop regions, and FN (False Negative) stand for the regions of the crop misclassified by the model. The total Accuracy of the system is given by:

$$\text{ACCURACY} = TP+TN/TP+TN+FP+FN$$

Accuracy alone may not reflect class imbalance; therefore, Precision and Recall are also considered:

$$\text{PRECISION}=TP/TP+FP$$
$$\text{RECALL}=TP/TP+FN$$

Precision measures how many predicted crop areas are actually crops, and Recall measures how many actual crop areas correctly identified. The F1 Score, which combines both Precision and Recall, is defined as:

$$F1 = 2\times (\text{Precision} \times \text{Recall} / \text{Precision} + \text{Recall})$$

The performance of each model is validated using a test data set. The metrics provide a measure of detection capability and allow a comparison with existing systems.

E. Database Creation.

An organized land database was created to link survey numbers with satellite images and crop details.
It stores survey number, latitude, longitude, registered crop name, and image reference for each land parcel. The user enters a survey number to retrieve the related data from the database.

F. GUI Development.

A graphical user interface (GUI) was developed in MATLAB to allow users to upload a satellite image and get crop classification results. The GUI displays the predicted crop type and its output, making the system easier to use even for non-technical users

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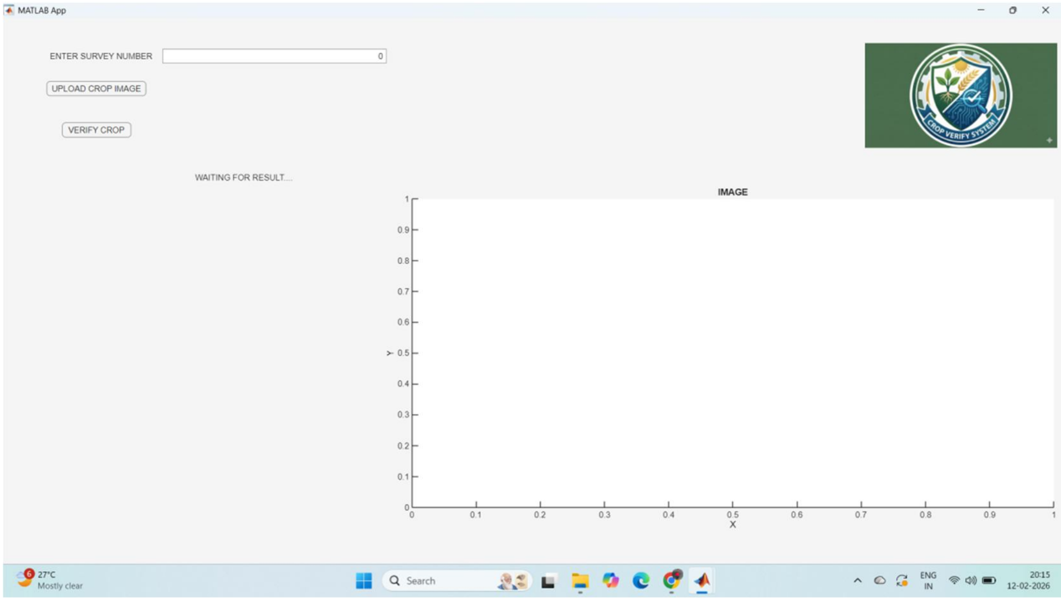

Fig. 3 GUI Development

IV. REAL-WORLD DEPLOYMENT FRAMEWORK

In an actual case scenario, the system may be connected to a digital database of land records whereby a land parcel is uniquely identified by its survey number, geographic coordinates, boundary polygon, and administrative details. Upon entry of the survey number, the land boundary will be retrieved, and the coordinates will then be used to query satellite images from authorized sources such as Google Earth Engine, USGS Landsat, and Copernicus Sentinel via secure API keys. Cloud filtering will then be employed to fetch images with clear conditions; in case higher resolution images are required, Landsat images of 30m resolution and Sentinel-2 images of 10m resolution may be employed. These may be clipped to the exact land parcel and processed using various bands ranging from Blue, Green, Red, NIR, to SWIR. Additionally, the images may be processed to remove clouds, corrected, stacked, normalized, resized to desired size to fit the input size of the models, and may also employ vegetation indices to improve crop discrimination.

This satellite image will be analyzed by the pre-trained and fine-tuned models specific to crop prediction in the visible spectrum – Blue, Green, Red, NIR, and SWIR bands. The outcome, along with survey number, satellite source, and date, is stored in the database, which can be used to generate verification reports for banks, insurance agencies, or government organizations. Such a mechanism facilitates automated, scalable, and intelligent crop verification without requiring inspection of the field.

V. RESULTS AND DISCUSSION

A. Experimental Setup

The research study used an experiment method to train various pre-trained CNN models such as ResNet-18, GoogLeNet, SqueezeNet, MobileNetV2, InceptionV3, ResNet50, and ResNet101 on a crop classification problem using satellite images based on survey numbers. All models were trained using the same conditions for a fair comparison. The study compared the three hyperparameter optimization techniques Adam, SGDM and RMSprop, on convergence and prediction performance of the CNNs. The training process ran for 5,10,15,20,25 epochs with a fixed learning rate schedule. From a careful comparison, it was found that ResNet-101 with 25 Eppoch along with the Adam optimizer dominated over all other combinations. With respect to acquiring the optimal configuration, during training, it has been found that running ResNet-101 along with Adam, keeping the learning rate at 0.001, results in better convergence rates than any other combination. Thus, based on quantitative evaluation metrics, ResNet-101 along with Adam has been selected as the final model for the proposed system. The proposed model yielded a high rate of overall classification accuracy for the test dataset. The values of precision and recall for most crop classes were almost balanced, showing consistency in recognition without biasing any class over others. This is further validated by the F1-score. In the confusion matrix, it is seen that most of the crops were correctly classified. There was minor confusion between crops of similar texture or growth stages. For example, similar vegetation types showed a degree of overlap between them. However, different crops like barren land were classified with a high degree of accuracy.

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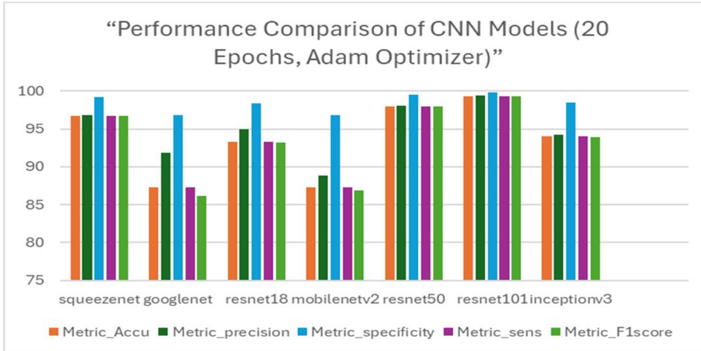

Fig. 4 comparison between different models

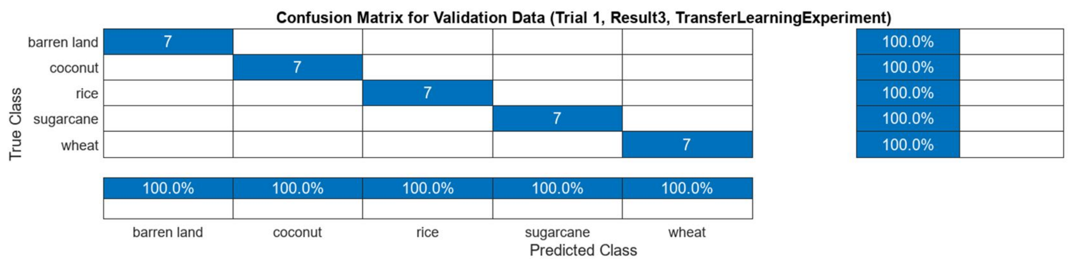

Fig. 5 confusion matrix for validation data

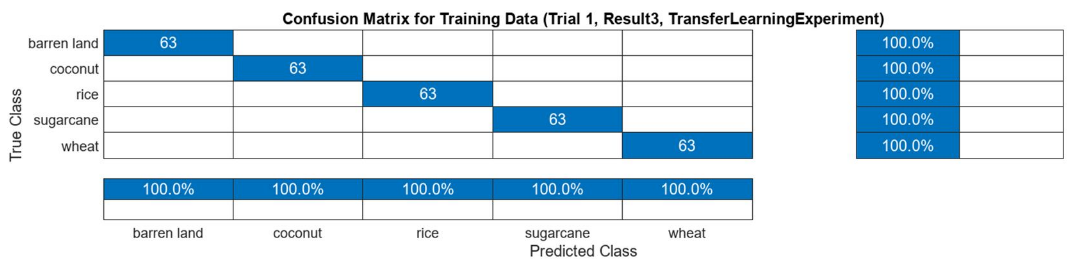

Fig. 6 confusion matrix for training data

B. *Verification Performance*

When the system was integrated with the survey number database, it successfully compared the predicted labels of the crops with the registered crop information. The system indicated a large number of "Pass" for correct matches and correctly indicated incorrect matches "Fake."

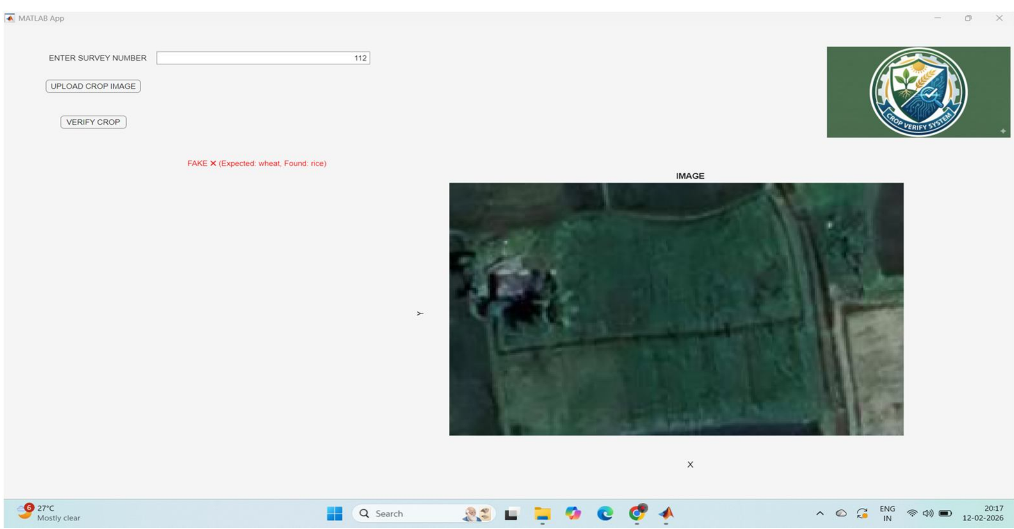

Fig. 7 crop classification and survey number verification

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VI. FUTURE SCOPE AND CONCLUSION

The proposed system infers that satellite image usage in conjunction with AI technology and classification is instrumental in the detection of crop patterns and verification of potential crop mismatch using the survey number approach. The combined usage of image processing and machine learning algorithms in the model makes it a more organized and mechanized approach toward the verification of agricultural land. The evaluation results confirm the feasibility of the proposed system, as it increases the accuracy, precision, recall, and F1-score values of the model for effective usage in the verification process. For the future, this system can be improved by incorporating the use of multi-temporal satellite image time series to identify crop variations seasonally. The usage of high-resolution images and deep learning models like attention-based networks can improve the accuracy of the system. The inclusion of real-time satellite API services and government land record database services can make this system fully automated. Moreover, the extension of this model to detect crop health, yield estimation, and crop anomalies can make this system more valuable for agricultural management systems and for verifying financial systems.

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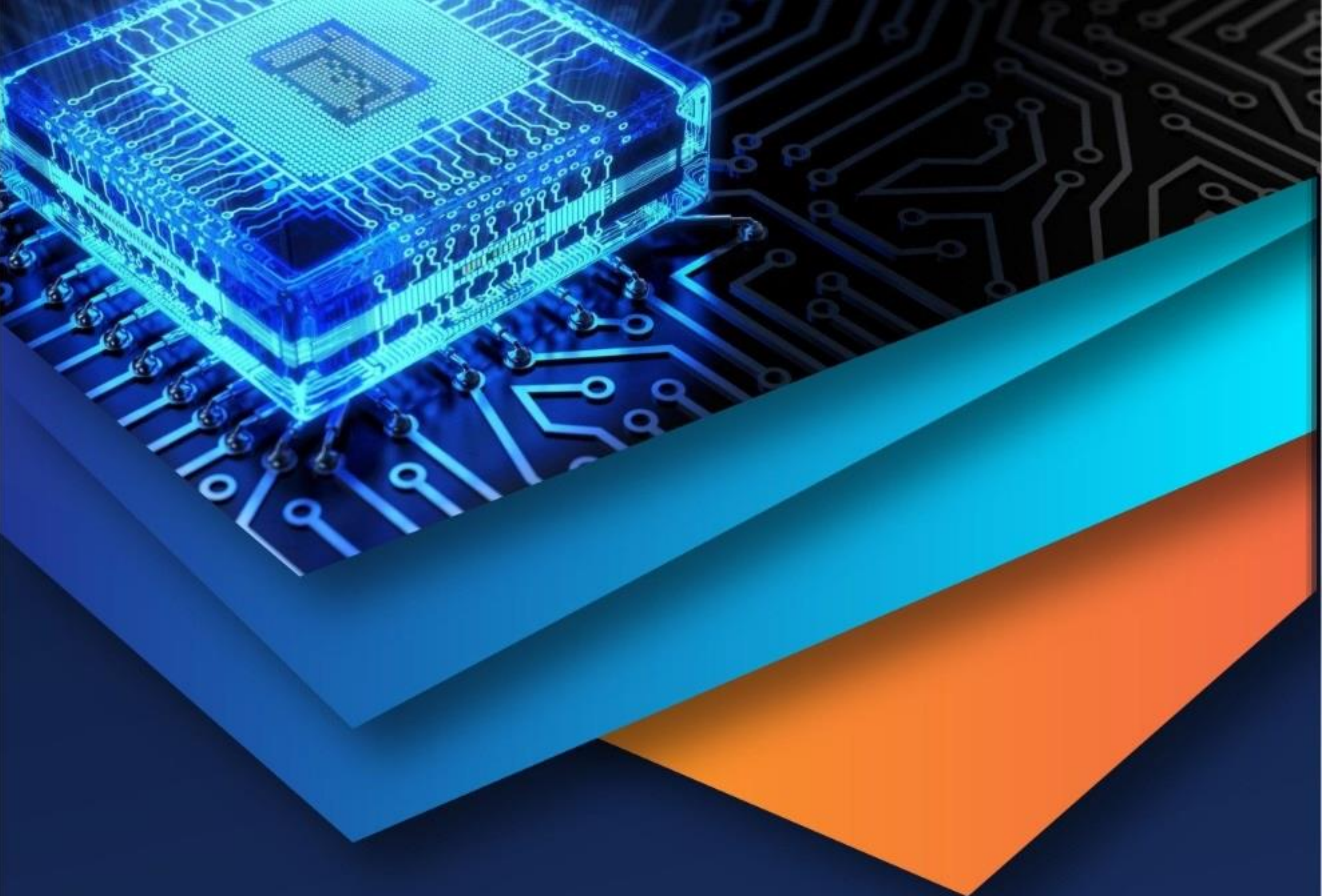

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