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Deep Learning in Arecanut Research: A Comprehensive Survey

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Abstract: Arecanut (betel nut) is an important tropical crop grown mainly in India, which ranks second worldwide in its production and consumption. However, Arecanut plants face numerous diseases affecting their leaves, trunks, roots, and fruits, some of which are hard to detect visually. However, its production is severely threatened by various leaf and nut diseases, particularly Yellow Leaf Disease (YLD), which causes substantial economic losses. Early and accurate disease detection is therefore crucial for ensuring sustainable cultivation. Recent advancements in machine learning and deep learning have enabled automated approaches for identifying, classifying, and predicting Arecanut diseases through image-based analysis. This survey paper provides a comprehensive review of existing works ranging from conventional image processing techniques to modern (CNNs) and transfer learning models such as MobileNetV2, ResNet, and VGG-16. Studies have demonstrated the effectiveness of hybrid methods combining CNN with SVM, as well as region-specific assessments of disease severity. Additionally, research on causal agents of YLD and spatial disease pattern analysis highlights the growing role of AI in precision agriculture. By comparing methodologies, datasets, and performance metrics across multiple studies, this paper identifies current challenges such as limited annotated datasets, variations in environmental conditions, and the need for real-time mobile applications. Finally, it outlines potential research directions including multimodal disease prediction, lightweight deep learning models for deployment on edge devices, and integration with Internet of Things (IoT)-based monitoring systems to achieve scalable and farmer-friendly solutions.

Keywords: Yellow leaf classification, Arecanut yellow leaf disease, Convolutional Neural Network (CNN), Deep learning, Agricultural technology, Image processing.

I. INTRODUCTION

A. History of Arecanut Cultivation

Arecanut has been cultivated for centuries, especially in South and Southeast Asia, with India being one of the largest producers. The crop is culturally significant and economically vital in regions like Karnataka and Kerala, where many farmers depend on it for their livelihood [2]. Over time, cultivation practices evolved from traditional farming to include scientific approaches, aiming to improve yield and disease management [1].

B. Importance of Arecanut

As a major crop, Arecanut supports millions of farmers and contributes significantly to India's agricultural economy. It is also used widely in cultural practices and as a commercial product.

C. Different Types of Diseases Affecting Arecanut

1) *Yellow Leaf Spot:* Occurs mainly during the southwest monsoon, affecting young palms. It causes dark spots with yellow halos on leaves, leading to drying and leaf drop if untreated Fig. 1 [5].

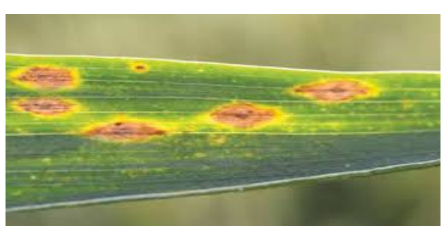

Fig. 1. Yellow Leaf Spot

2) *Yellow Leaf Disease:* This condition turns the leaflets pale yellow and dry, gradually weakening the palm and lowering yield Fig. 2 [12].

Fig. 2. Yellow Leaf Disease

3) *Mahali/Koleroga (Fruit Rot):* A fungal infection that attacks tender nuts during the rains, making them rot and fall off early Fig. 3 [12].

Fig. 3. Mahali/Koleroga

D. Methods

The proposed approach Fig. 4 starts with collecting and cleaning Arecanut images to build a dependable dataset. These images are then processed to extract important features, which are used to train deep learning models like CNNs for accurate disease detection. In the final stage, the model is tested for performance and deployed for real-time use in monitoring and supporting farmers [7].

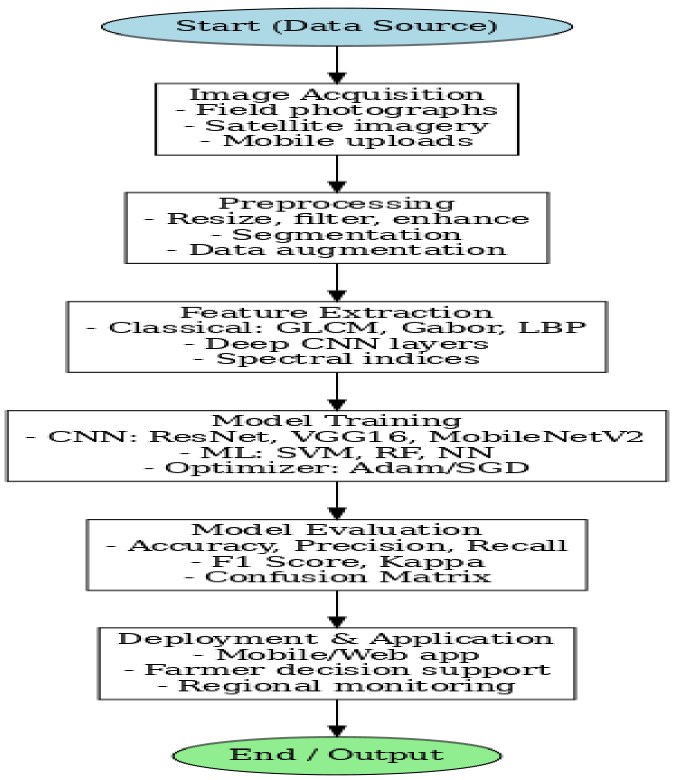

Fig. 4. Working Flowchart

- Data Acquisition **-** Images are collected from field photographs, satellite imagery, or mobile uploads.
- Preprocessing **-** Images are resized, filtered, segmented, and augmented to enhance quality and variety.
- Feature Extraction **-** Classical methods (GLCM, Gabor, LBP), deep CNN layers, or spectral indices are used.
- Model Training & Evaluation **-** Models such as CNNs (ResNet, VGG16, MobileNetV2) or ML classifiers (SVM, RF) are trained and tested using metrics like accuracy, precision, recall, F1, and Kappa.
- Deployment & Application **-** Final models are deployed in mobile/web apps for farmer decision support and regional disease monitoring.

II. BACKGROUND

Arecanut is an economically significant crop in India and Southeast Asia, but it is vulnerable to a variety of diseases such as fruit rot (Mahali/Koleroga), stem bleeding, bud borer, nut split, and the widely prevalent Yellow Leaf Disease (YLD). Manual disease detection relies heavily on expert inspection of plantations, which is time-consuming, labour-intensive, and often error-prone, particularly in large-scale cultivation areas. In the Malenadu region, leaf spot and YLD are of major concern due to their widespread impact on productivity and farmer livelihoods. Epidemiological surveys and severity mapping have shown that disease outbreaks lead to serious economic losses, yet traditional survey methods remain slow and fragmented. Historical studies on YLD highlight debates over its causal agents—ranging from phytoplasma to viral pathogens such as Areca palm velarivirus 1 (APV1)—and emphasize the need for better monitoring tools. Conventional image-processing approaches, using texture features with classifiers like SVM, have been explored, but they often lack robustness under field variability. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), offer higher accuracy in plant disease detection by learning discriminative features directly from images.

Field-based datasets, such as collections of ~700 arecanut leaf images across disease classes, now enable experimental comparisons of lightweight versus deeper CNN architectures. Complementary to ground-level monitoring, remote sensing approaches using medium-resolution imagery (e.g., PlanetScope, 3 m) allow regional-scale detection of YLD severity. Integrating biological knowledge, epidemiological field studies, and AI-based approaches thus presents a promising direction toward precision agriculture in Arecanut disease management.

A. Problems with Traditional Disease Detection

Traditional Arecanut disease detection still depends largely on manual inspection by farmers or agricultural experts. This process is time-consuming and labour-intensive, requiring specialized knowledge to recognize early symptoms accurately. Human error and delays often reduce reliability, making early detection difficult. Moreover, manual methods cannot be scaled effectively across large plantations. These limitations delay timely intervention, which in turn allows diseases to spread further and result in considerable crop losses.

B. Deep Learning

Recent studies on Arecanut disease detection employ CNNs and transfer learning models (ResNet, VGG16, MobileNetV2, EfficientNet) trained on custom datasets (~180–888 images) with preprocessing steps like resizing, normalization, and augmentation [6]. Typical architectures use Conv2D, pooling, dropout, and dense layers, optimized with categorical cross-entropy and Adam, trained for 20–100 epochs. CNNs consistently outperform classical methods (SVM, RF, AdaBoost) based on handcrafted features (GLCM, Gabor, LBP), achieving accuracies above 90%. Biological insights and spectral indices (PSRI, EVI) have also been integrated to improve interpretability and remote-sensing applications. Overall, CNN-based transfer learning provides the most scalable and accurate framework for automated Arecanut disease detection.

C. Metrics

To evaluate the performance of machine learning and deep learning models for arecanut disease detection, researchers have employed several standard classification metrics. These metrics provide insights into how accurately the models can distinguish between healthy and diseased samples. Overall, accuracy, precision, recall, and F1-score remain the most widely adopted metrics in arecanut disease detection research, with some studies additionally incorporating ROC curves and confusion matrices for deeper performance analysis[9].

D. Tools and Framework

Arecanut disease detection studies use Python as the primary language, with MATLAB applied in some cases for prototyping. Deep learning frameworks such as TensorFlow and Keras support CNN development, while OpenCV handles preprocessing tasks like resizing, normalization, and augmentation. Classical ML classifiers (SVM, RF, AdaBoost) are often implemented using scikit-learn, with Adam and categorical cross-entropy as standard training setups. Using transfer learning with pretrained models such as ResNet, VGG16, MobileNet, and InceptionV3 helps improve accuracy, especially when working with smaller datasets. In addition, remote sensing techniques that combine PlanetScope imagery, spectral indices, and feature selection provide valuable insights for monitoring crops. To make these technologies more practical, web and mobile applications are also being developed to support farmers in decision-making and to integrate with Integrated Pest Management (I3PM) practices [13].

III. RELATED LITERATURE SURVEY

Table I
Summary of Arecanut Disease Detection Studies

Reference (Author, Year)	Image Count	Method	Datasets	Advantages	Limitations
Ajith Hegde - 2023	1,100 images	CNN (Adam optimizer, BCE loss)	Proprietary dataset	High detection accuracy with robust CNN model architecture.	Relies on a relatively small and localized dataset.
Arun Karthik V - 2024	500 images	CNN (deep learning, categorical classification)	Custom dataset (Arecanut leaves, 80:20 split)	Automates disease detection.	Limited dataset size, geographic coverage.
Dhanuraj K C - 2020	700 images (7 classes)	Texture features (Wavelet, Gabor, LBP, GLDM, GLCM) + Nearest Neighbour	Proprietary dataset	Works without experts and supports large-scale image processing.	Cannot detect disease in hidden or covered areas.
Jiawaie Guo - 2022	Large-scale satellite coverage (PlanetScope, 3m resolution)	RF (best), BPNN, AdaBoost	Planet Scope satellite images (spectral features)	Allows efficient, regional disease monitoring with 3 m resolution.	Lacks detailed technical comparisons.
Latif Ullah Khan - 2023	1000 images	Review of Yellow Leaf Disease (YLD) causal agents	Kaggle dataset	Offers a comprehensive synthesis of decades of research.	Does not present new experimental data.
Madhu B G - 2024	RGB images (count not given)	ResNet (with global average pooling)	Custom dataset of arecanut images	High accuracy and robustness due to use of ResNet and large dataset.	Relies on quality and diversity of the self-collected dataset.
Prajwal Annasab - 2023	888 images	CNN (Adam optimizer, categorical cross entropy)	Custom dataset (healthy & diseased Arecanut, 80:20 split)	High accuracy and reliability using ResNet and a large dataset.	Depends on the quality and variety of the collected dataset.
Premalatha K- 2024	Field survey data	Statistical disease scoring & incidence intensity	Field survey in Karnataka plantations	Field-based, large-scale data collection improves real-world relevance.	Study is observational and does not investigate causative factors or control measures.
Shreedhar N Hegde-	250 images	Machine Learning	Custom dataset	Combines survey data	Dataset from

Reference (Author, Year)	Image Count	Method	Datasets	Advantages	Limitations
2025		(CNN for severity assessment)	(Malenadu region, leafspot images)	with AI for strong validation	Malenadu only — may not suit other climates
Mamatha Balipa - 2022	180 images	CNN with handcrafted features + SVM	Custom-collected dataset	Reduces labor and ensures consistent diagnosis.	Small dataset may limit general use.

The reviewed studies on Arecanut disease detection utilized datasets ranging from small self-collected image sets to large-scale satellite imagery. Deep learning models such as CNN, ResNet, and ensemble approaches were widely adopted, consistently demonstrating strong performance in disease classification. In contrast, traditional feature-based methods like Gabor, LBP, and GLCM, along with machine learning techniques such as SVM, Random Forest, and AdaBoost, were explored mainly as baselines. However, several works pointed out challenges such as limited dataset size, region-specific data, and lack of standardization, which restrict model generalization. Overall, CNN-based approaches showed superior accuracy, while satellite imagery and statistical surveys extended the application of disease detection to regional and field-level monitoring.

Table II
Comparison of Datasets, Methods, Results in Arecanut Disease Detection Studies

Paper (Author, Year)	Dataset Details	Diseases Addressed	Model/Algorithm	Main Results/Accuracy
Ajith Hegde - (2023)	1,100 images (proprietary, healthy & diseased)	Fruit rot, stem bleeding, yellow leaf spot, nut split	CNN	Accuracy: 93.05%
Arun Karthik V - (2024)	620 images (healthy/diseased, regional)	Mahali, stem bleeding, bud rot	CNN	Accuracy: 88.46%; F1: 88.5%
Dhanuja K C - (2020)	700 images, texture features	Multiple classes	Texture features + NN	Gabor features: 91.43%
Jiawei Guo - (2022)	Satellite imagery and field survey (China)	Yellow leaf disease	RF, BPNN, AdaBoost (spectral)	RF accuracy: 88.24%
Latif Ullah Khan - (2023)	Literature review (pathogen focus)	Yellow leaf disease	Biology/Virology	Summary of APV1, phytoplasma, symptoms
Madhu B G - (2024)	1200 images (augmented 11,063), healthy/diseased	Koleroga, stem bleeding, yellow leaf, stem cracking	ResNet (CNN)	Accuracy: 97.5%
Prajwal A - (2023)	888 images (collected), healthy/infected	Koleroga, nut split, stem bleeding, yellow leaf spot	CNN	Accuracy: 88.46%
Premalatha K - (2024)	Extensive field survey (Karnataka, India)	Yellow leaf disease	Field scoring, intensity calc	Incidence: up to 100% in high-risk taluks
Shreedhara N Hegde - (2025)	250 images (severity focus, Malenadu region)	Leaf spot (Colletotrichum spp., Phyllotactic, Pestalotia)	CNN, SVM	CNN: 94% accuracy
Mamatha Balipa - (2022)	181 images, textural (healthy/diseased)	Koleroga, stem bleeding, yellow leaf mark	CNN, SVM	CNN: 90%, SVM: 75%

Paper (Author, Year)	Dataset Details	Diseases Addressed	Model/Algorithm	Main Results/Accuracy
Sneha Chikkanayakanahalli - (2025)	8,844 images (Kaggle + field)	Koleroga, stem bleeding, yellow leaf.	CNN (ResNet, NasNet)	Max accuracy: 98.9% (CNN w/extension)
Yusliza Yusoff - (2023)	Survey of 100+ literature	Various (general plant leaf diseases)	CNN, SVM, KNN, GLCM	Review (not empirical, summary stats)
Beena K - (2024)	620 images (manual, healthy/diseased leaves, trunk, nut)	Mahali, stem bleeding, ring spot, yellow leaf spot	VGG16, ResNet, MobileNetV2	ResNet: 92%, VGG16: 88%, MobileNetV2: 87%

The reviewed studies on Arecanut disease detection highlight the effectiveness of deep learning models, particularly CNN-based approaches, in achieving high accuracy (up to 97%). Traditional methods like feature extraction, RF, and SVM showed moderate performance, while modern architectures such as ResNet and VGG further improved reliability. Most research used region-specific datasets with limited size, which may restrict generalization. Overall, CNN and hybrid deep learning techniques demonstrate strong potential for automated, accurate, and scalable Arecanut disease identification

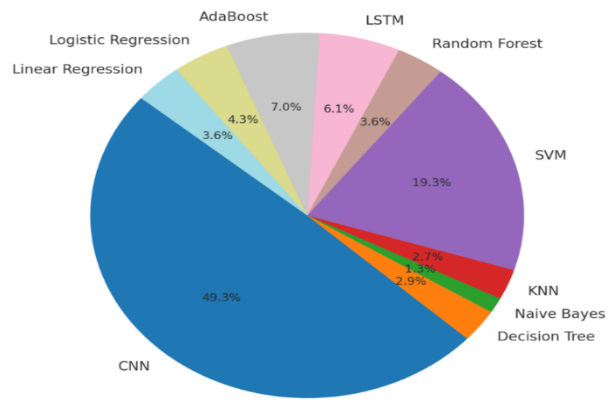

Fig. 5. Model Usage Distribution in Plant Disease Detection Studies

As shown in the Fig 4.1 illustrates the application of different machine learning models for detecting Arecanut Yellow Leaf Disease (YLD). Convolutional Neural Networks (CNN) dominate with 49.3%, showing their strong ability in handling image-based classification tasks and achieving higher accuracy compared to other methods. Support Vector Machines (SVM) account for 19.3%, making them the second most widely used model due to their effectiveness in dealing with non-linear and complex data patterns. Moderate contributions are made by AdaBoost (7%), LSTM (6.1%), and Logistic Regression (4.3%), which provide additional approaches but are less dominant. Traditional models like Decision Trees, Naive Bayes, and K-Nearest Neighbors show lower adoption rates, each contributing less than 3%. Overall, the chart highlights that deep learning models, particularly CNN, play a crucial role in reliable and accurate detection of Arecanut Yellow Leaf Disease.

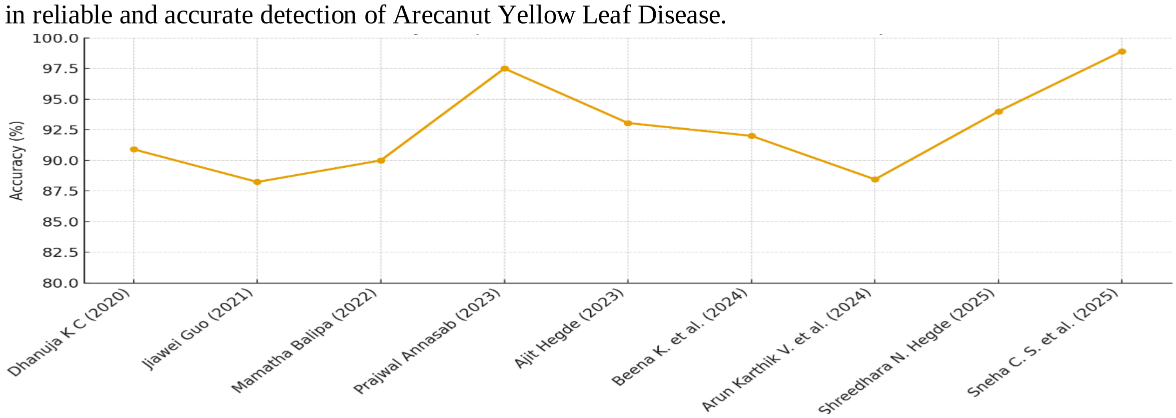

Fig. 6. Accuracy Trends in Arecanut Disease Detection Models

The line graph in Fig 4.2 presents the accuracy comparison of research papers on Arecanut disease detection from 2020 to 2025. The trend shows a steady improvement in model performance over time. Early studies, such as Dhanuja K C (2020) and Jiawei Guo (2021), achieved accuracies around 90%, while more recent works like Ajit Hegde (2023) and Sneha C. S. et al. (2025) reached peak values close to 98–99%. Mid-phase studies (2022–2024) demonstrated stable results above 92%, highlighting progressive refinements in methodology and model selection. The graph clearly shows that recent advancements in deep learning, especially CNN-based methods, have played a key role in improving the accuracy of Arecanut disease detection. [5].

IV. CHALLENGES

1) Dataset Limitations
2) Image Quality & Preprocessing Issues
3) Model Challenges
4) Evaluation & Metrics
5) Tools & Framework Issues
6) Deployment Challenges
7) Biological & Ground Truth Challenges
8) Scalability & Generalization

V. CONCLUSION

The reviewed studies show that both machine learning and deep learning methods have strong potential in detecting and classifying Arecanut diseases. Convolutional Neural Networks (CNNs) and their variants, such as ResNet, VGG16, MobileNetV2, and EfficientNet, consistently outperformed traditional techniques like SVM, Random Forest, and Backpropagation Neural Networks. Reported accuracies usually ranged between 85% and 95%, with some models achieving almost perfect performance under controlled conditions. Transfer learning and data augmentation proved especially useful in overcoming the challenges of small datasets. Feature-based methods like GLCM, Gabor, and LBP provided valuable baselines, while the use of satellite imagery extended detection to plantation-level monitoring. Pathology-focused studies also highlighted the biological complexity of Yellow Leaf Disease (YLD), showing the need for accurate labelling and interdisciplinary approaches. Despite these advances, several challenges remain. Most datasets are still small, region-specific, and restrict the generalization of models. Many studies emphasized accuracy, while paying less attention to precision, recall, or real-world validation. Overfitting also remains a recurring problem due to limited data diversity. In addition, practical deployment aspects—such as mobile applications, offline usability, and decision-support tools for farmers—are still at an early stage. Addressing these gaps will require larger and more diverse datasets, along with hybrid models that integrate biological, climatic, and imaging data.

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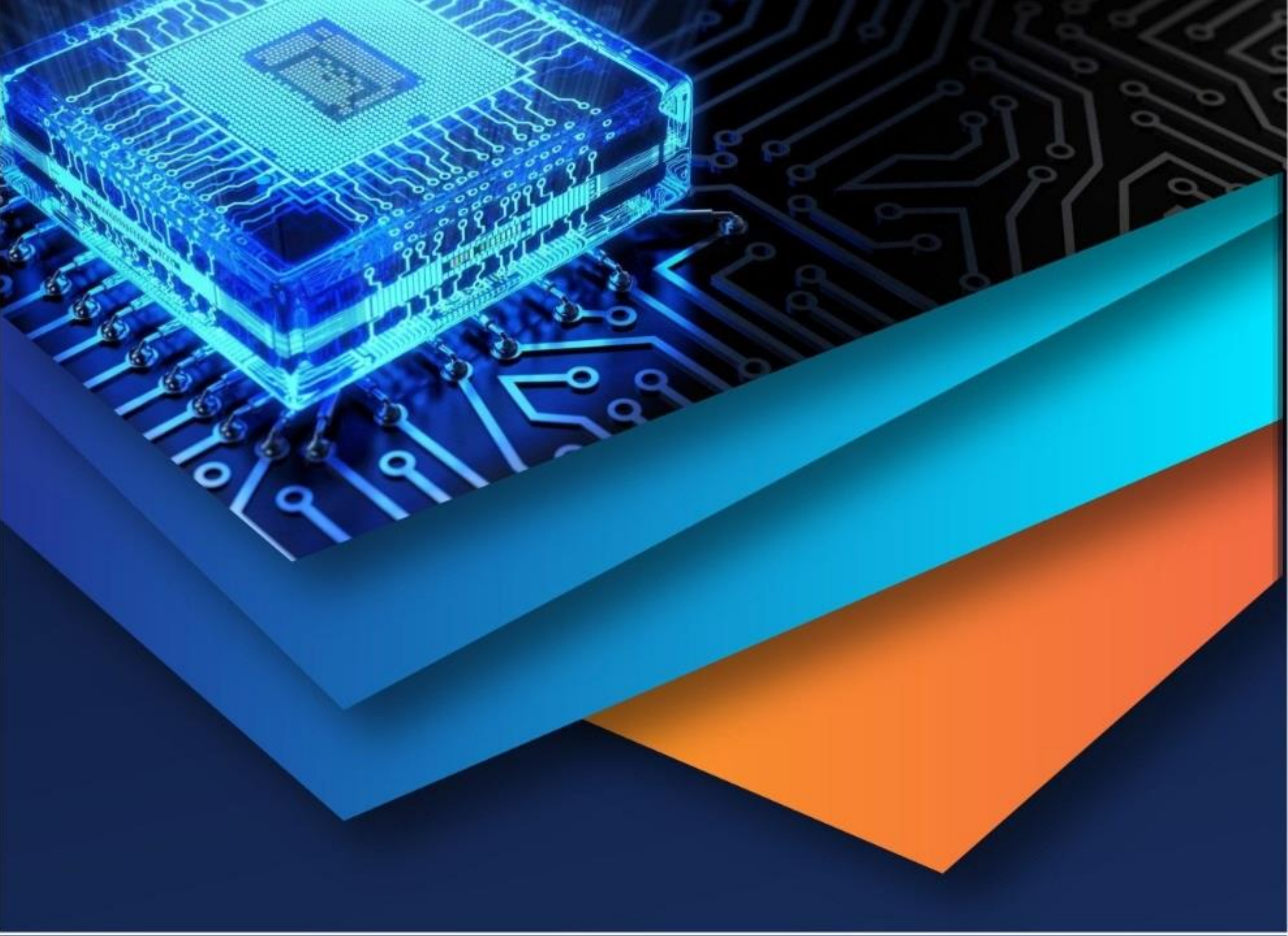

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