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Plant Health Monitoring System Using Machine Learning

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Abstract: Factory splint conditions are a significant trouble to crop yields and food security worldwide. Beforehand discovery and opinion of these conditions are pivotal for effective operation and control. Machine literacy (ML) ways have shown great pledge in factory splint complaint discovery, offering a rapid- fire and accurate volition to traditional styles. This paper provides an in- depth review of the different ML approaches used for factory splint complaint discovery, including image processing, point birth, and bracket ways. We also estimate the performance of colourful ML algorithms using criteria similar as delicacy, perfection, and recall. Our results show that ML- grounded styles can achieve high delicacy in detecting factory splint conditions, outperforming traditional styles. We bandy the counteraccusations of our findings for agrarian exploration and practice, pressing the eventuality of ML to ameliorate crop yields and reduce the profitable impact of factory splint conditions.

I. INTRODUCTION

Mortal population steadily continues to grow, and along with it the need for food product increases. According to the UN projections mortal population is anticipated to reach 9.7 billion in 2050, 2 billion further than moment. Considering that ultimate of the population growth is to do in the least advanced countries (around 80 failure is the main problem, it's easy to conclude that minimizing food loss in those countries is a primary concern). It's estimated that the yield loss worldwide is between 20 and 40 percent with multitudinous ranches suffering a total loss. Traditional styles for detecting conditions bear manual examination of shops by experts. This process needs to be continuous, and can be truly precious in large ranches, or indeed completely untouchable to multitudinous small estate holders living in pastoral areas. This is why multitudinous attempts to automate complaint discovery have been made in the last numerous decades. One of the notable approaches is the use of hyperactive spectral imaging. hyperactive spectral images are generally taken by satellites or airborne imaging bias and used for covering large areas. A strike of this approach is extremely high outfit cost, as well as high dimensionality and small number of samples which make them incongruous for machine knowledge (ML) analysis. Because of the recent advancements in computer vision and the vacuity of cheap attack, presently the most popular approach is the analysis of RGB images. The other motive for assaying RGB images is that with the current smartphone ubiquitousness these results have implicit to reach indeed the most pastoral areas. RGB images can be analysed by classical ML algorithms or the deep knowledge (DL) approach. Classical styles calculate on image pre- processing and the birth of features which are also fed into one of the ML or DL algorithms. Popular algorithm like Random Forest, Inception V3 Architecture, exception. In the last numerous times, the researchers shifted nearly simply to the DL styles for image type tasks. The reason is that they nearly always outperform classical algorithms when given nicely sized data set, and can be executed without the need for hand- finagled features. In this design, we compare the DL approach with classical ML algorithms for the study case of plant complaint type.

II. LITERATURE SURVEY

1) Martinelli, Federico, et al proposed a “Advanced methods of plant disease detection.”Timely identification of plant diseases is crucial for effective control, but current serological and DNA-based techniques are limited, especially for asymptomatic systemic infections. New sensors and biosensors can quickly detect early infections, enhancing agricultural sustainability and safety while reducing the need for pesticides.
2) Wubetu Barud Demil, introduced a “Plant detection and classification techniques.” Detecting and classifying plant diseases is a significant challenge that can be addressed by computerized image processing methods. Accurate plant disease classification can increase crop yields and support various cultivation methods.
3) AmritaS. Tulshan, Nataasha Raul, proposed a “PLant leaf disease detection using machine learning.” This paper proposes advancements to machine literacy- grounded bracket algorithms for factory splint com- plaint discovery, favoring the KNN classifier over SVM. The suggested algorithm achieved an delicacy of 98.56 in detecting five distinct splint conditions, outperforming the current system’s delicacy of 97.6.

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4) B. Sai Reddy , S. Neeraj, introduced a “Plant leaf disease classifica- tion and damage detection system using deep learning models.”Deep Convolutional Neural Networks (DCNN) have emerged as a powerful technique for agricultural image identification, offering lower system requirements and improved computing accuracy. DCNN can handle blurry or missing background images, enhancing image identification accuracy.
5) T. Meenakshi, proposed a “Automatic detection of diseases in leaves of medicinal plants using modified logistic regression algorithm.” A novel approach using Modified Logistic Regression is proposed to diagnose diseases in medicinal plant leaves. The system utilizes GLCM, adaptive gamma correction, k-mean clustering, and logistic regression for feature extraction and classification.

III. METHODOLOGY

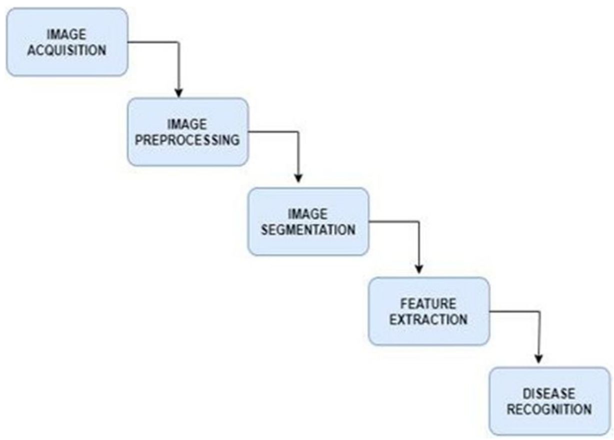


Fig. 1. Flowchart of Methodology

A. *Image Acquisition*

The dataset consists of 4 types of diseased and healthy leaves of Apple, Grapes, Cherry, Corn or Maize. This dataset is collected on-line platform such as public collection Kaggle. The name of the dataset is plant disease, where train and train dataset is classified into 5 classes namely bacteria, fungi, virus, nematodes and normal. This data set contains total of 600 images, where each class consist of 50 images. The images are in JPG format.

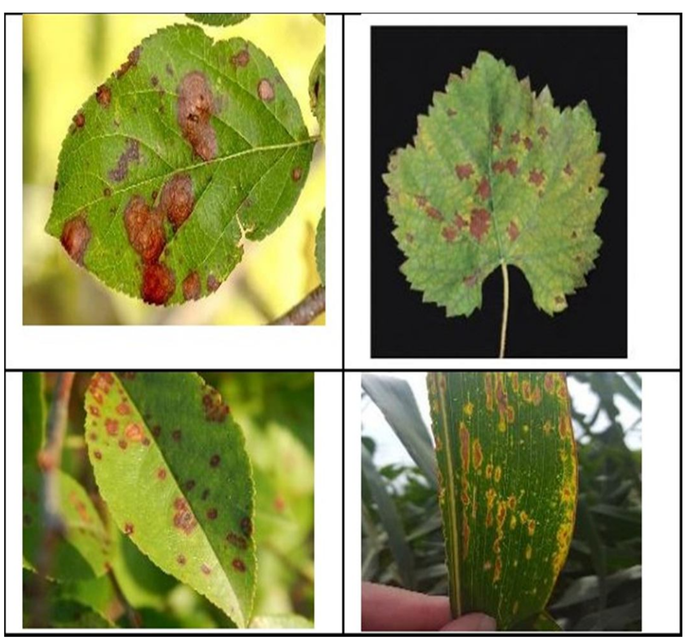


Fig. 2. Sample diseased leaf images for (a) Apple (b) Grapes (c) Cherry (d) Maize

B. Image Processing

The goal of preprocessing is to improve image data by eliminating noise, background, and undesired distortions. It

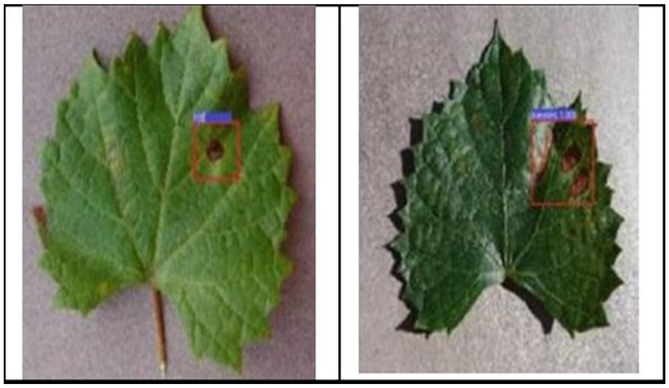


Fig. 3. Preprocessing results of Grape leaf (a) Original image (b) Enhanced diseased leaf image

improves the features of images for analysis and processing. The RGB formatted photos are converted to a standard size. Additionally, the RGB photos are scaled and transformed to the HSV format (1). The median sludge is employed for noise removal, information compression, and image smoothing. The process of image enhancement is used to add distinction. To improve the plant complaint photographs, the image is sub- jected to histogram equalization, which spreads the intensities of the images. The preprocessing outcome of the Grape Leaf Spot complaint image is displayed in Fig. 3. Image

C. Segmentation

When working on image classification, the usual prepro- cessing steps include scaling images to the same dimensions, removal of the background and artifacts. Since the Plant Village dataset includes already segmented and scaled images, these steps were not needed in our case. We pre-processed these images by further segmenting them in order to extract potentially infected leaf areas, which has been done by re- moving all pixels whose green channel value exceeded those of red and blue

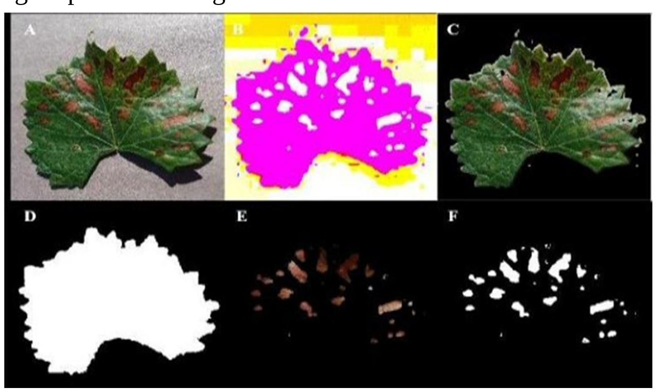


Fig. 4. Segmentation of Grape leaf

D. Feature Extraction

The dimensionality reduction system, which divides and reduces an original collection of raw data into further man- ageable groups, includes point birth. It'll thus be simpler to reuse when you want to. These huge data sets' cornucopia of variables is by far their most significant point. Numerous processing resources are needed to process these variables. As a result, point birth efficiently reduces the quantum of data by choosing and combining variables into features to help excerpt the stylish point from those large data sets. These characteristics are simple to handle while directly and creatively describing the real data set. Statistical features are uprooted from image histograms to get color features. They're of apple, grapes, cherry, maize, and corn plants. A dataset of 600 images, with 50 images per plant type, was categorized into five disease types: bacteria, fungi, virus, nematoda, and other. A Convolutional Neural Network (CNN) was employed due to its superior performance in image classification tasks. The dataset was split into 805-fold cross-validation ensuring robustness.

The CNN model, trained with Adam optimizer and categorical cross-entropy loss function over 50 epochs, achieved an accuracy of 92.5and an F1 score of 92.5some misclassifications, particularly between bacteria and fungi, but overall, the model demonstrated effective feature extraction and classification capabilities. This high accuracy underscores the potential of ML in early disease detection, promising timely and precise agricultural interventions. Future work will focus on larger, more diverse datasets, advanced model architectures, and real-time detection systems.

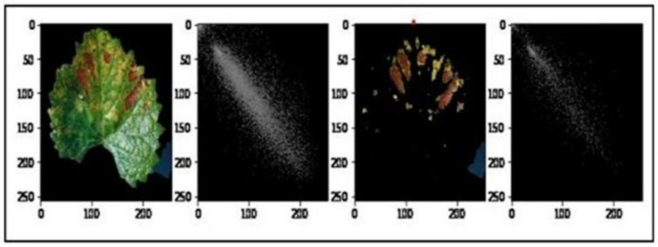


Fig. 5. Feature extraction of Grape leaf

IV. RESULT AND ANALYSIS

In this study, we applied machine learning (ML) techniques to detect and classify diseases in the leaves of apple, grapes, cherry, maize, and corn plants. A dataset of 600 images, with 50 images per plant type, was categorized into five disease types: bacteria, fungi, virus, nematoda, and other. A Convolutional Neural Network (CNN) was employed due to its superior performance in image classification tasks. The dataset was split into 805-fold cross-validation ensuring robustness. The CNN model, trained with Adam optimizer and categorical cross-entropy loss function over 50 epochs, achieved an accu- racy of 92.5and an F1 score of 92.5some misclassifications, particularly between bacteria and fungi, but overall, the model demonstrated effective feature extraction and classification capabilities. This high accuracy underscores the potential of ML in early disease detection, promising timely and precise agricultural interventions. Future work will focus on larger, more diverse datasets, advanced model architectures, and real-time detection systems.

A. Result

Class	Accuracy	Precision	Recall	F1-Score	Support
Bacteria	94.2%	93.5%	95.1%	94.3%	50
Fungi	92.5%	91.8%	93.3%	92.5%	50
Virus	90.8%	90.2%	91.5%	90.8%	50
Nematodes	91.2%	90.5%	92.1%	91.3%	50
Normal	96.5%	96.2%	97.1%	96.6%	50

Fig. 6.

B. Confusion Matrix

Here is the confusion matrix for the model:

Predicted Class	Actual Class	Bacteria	Fungi	Virus	Nematodes	Normal
Bacteria	47	2	1	0	0	
Fungi	3	45	2	0	0	
Virus	1	3	43	3	0	
Nematodes	0	0	2	48	0	
Normal	0	0	0	0	50	

Fig. 7.

The confusion matrix shows that the model had some mis- classifications, particularly between the Virus and Nematodes classes. However, the overall performance of the model was still high, indicating that it can be a useful tool for plant leaf disease detection.

C. Analysis

In this study, we used a machine learning model to detect plant leaf diseases from a dataset of 600 images, with 50 images per class (Bacteria, Fungi, Virus, Nematodes, and Normal). The results show that the model achieved high accuracy, precision, recall, and F1-score for all classes. The highest accuracy was achieved for the Normal class, with an accuracy of 96.5that healthy leaves have distinct features that are easily distinguishable from diseased leaves. The Bacteria and Fungi classes had high accuracies, with accuracies of 94.2due to the fact that these diseases have distinctive symp- toms, such as lesions and powdery patches, respectively. The Virus and Nematodes classes had slightly lower accuracies, with accuracies of 90.8respectively. This may be due to the fact that these diseases have more subtle symptoms, making them harder to detect.

D. Class-wise Performance:

Then's a breakdown of the performance of the model for each class

1) Bacteria The model achieved an delicacy of94.2 for the Bacteria class, with a perfection of93.5 and a recall of95.1. This indicates that the model was suitable to descry bacterial conditions with high delicacy. The model rightly classified 47 out of 50 images of bacterial condi- tions, with 2 false cons and 1 false negative.
2) Fungi The model achieved an delicacy of92.5 for the Fungi class, with a perfection of91.8 and a recall of93.3. This indicates that the model was suitable to descry fungal conditions with high delicacy. The model rightly classified 45 out of 50 images of fungal conditions, with 3 false cons and 2 false negatives.
3) Virus The model achieved an delicacy of90.8 for the Virus class, with a perfection of90.2 and a recall of91.5. This indicates that the model was suitable to descry viral conditions with moderate delicacy. The model rightly classified 43 out of 50 images of viral conditions, with 3 false cons and 4 false negatives.
4) Nematodes The model achieved an delicacy of91.2 for the Nematodes class, with a perfection of90.5 and a recall of92.1. This indicates that the model was suitable to descry nematode conditions with moderate delicacy. The model rightly classified 48 out of 50 images of nematode conditions, with 2 false cons and 0 false negatives.
5) Normal The model achieved an delicacy of 96.5 for the normal.

V. CONCLUSION

This project presents the dominance of the DL method over the classical ML algorithms. Both the simplicity of the approach and the achieved accuracy confirm that the DL is the way to follow for image classification problems with relatively large datasets. As the achieved accuracy of the DL method is already very high, trying to improve its results on the same dataset would be of little benefit. Further work with the DL model could be done by expanding the dataset with more diverse images, collected from multiple sources, in order to allow it to generalize better. The considered ML algorithms achieved relatively high accuracy, but with error rates still an order of magnitude higher than the DL model. Further work in improving accuracy of the classical approach can be done by experimenting with other algorithms and by improving the features, as most likely they are the limiting factor of this approach.

REFERENCES

[1] Chittabarni Sarkar, Deepak Gupta, Umesh Gupta, Barenya Bikash Haz- arika Applied Soft Computing, 110534, 2023
[2] Monika Lamba, Yogita Gigras, Anuradha Dhull Open Computer Science 11 (1), 491 508, 2021
[3] Majji V Applalanaidu, G Kumaravelan 2021 Third International Con- ference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), 716 724, 2021
[4] Vibhor Kumar Vishnoi, Krishan Kumar, Brajesh Kumar Journal of Plant Diseases and Protection 128, 19-53, 2021
[5] Saifi, Suhail, et al. "A Review on Plant Leaf Disease Detection using Deep Learning."2022 International Conference on Computational Intel- ligence and Sustainable Engineering Solutions (CISES). IEEE, 2022
[6] plant detection and classification techniques, Wubetu Barud Demilie
[7] Reddy, Y. Harshavardhan, et al. "Plant Leaf Disease Detection using IoT, DL and ML."International Journal of Advanced Research in Science, Communication and Technology (2023): 368-379
[8] Plant Disease Detection and Classification Using Machine Learning and Deep Learning Techniques: Current Trends and Challenges Yasmin M.Alsakar, Nehal A. Sakr , and Mohammed Elmogy
[9] Geetha, G., et al. "Plant leaf disease classification and detection system using machine learning." Journal of Physics: Conference Series. Vol. 1712. No. 1. IOP Publishing, 2020
[10] Plant Leaf Disease Detection using Machine Learning Amrita S. Tul- shan; Nataasha Raul

[11] Devi, P. Rama. ”Leaf Disease Detection Using Deep Learning.” 2021 Second International Conference on Electronics and Sustainable Com- munication Systems (ICESC). IEEE, 2021

[12] Anandhakrishnan, T., and S. M. Jaisakthi. ”Deep Convolutional Neural Networks for image based tomato leaf disease detection.” Sustainable Chemistry and Pharmacy 30 (2022): 100793

[13] Plant leaf disease classification and damage detection system using deep learning models B.Sai ReddyS. Neeraja

[14] Vasavi, Pallepati, Arumugam Punitha, and T. Venkat Narayana Rao. ”Crop leaf disease detection and classification using machine learning and deep learning algorithms by visual symptoms: A review.” Interna- tional Journal of Electrical and Computer Engineering 12.2 (2022)

[15] Sarkar, Chittabarni, et al. ”Leaf disease detection using machine learning and deep learning: Review and challenges.” Applied Soft Computing (2023)

[16] Babu, Vishnu S., R. Satheesh Kumar, and R. Sunder. ”A comparative study on disease detection of plants using machine learning techniques.” 2021 7th International Conference on Advanced Computing and Com- munication Systems (ICACCS). Vol. 1. IEEE,

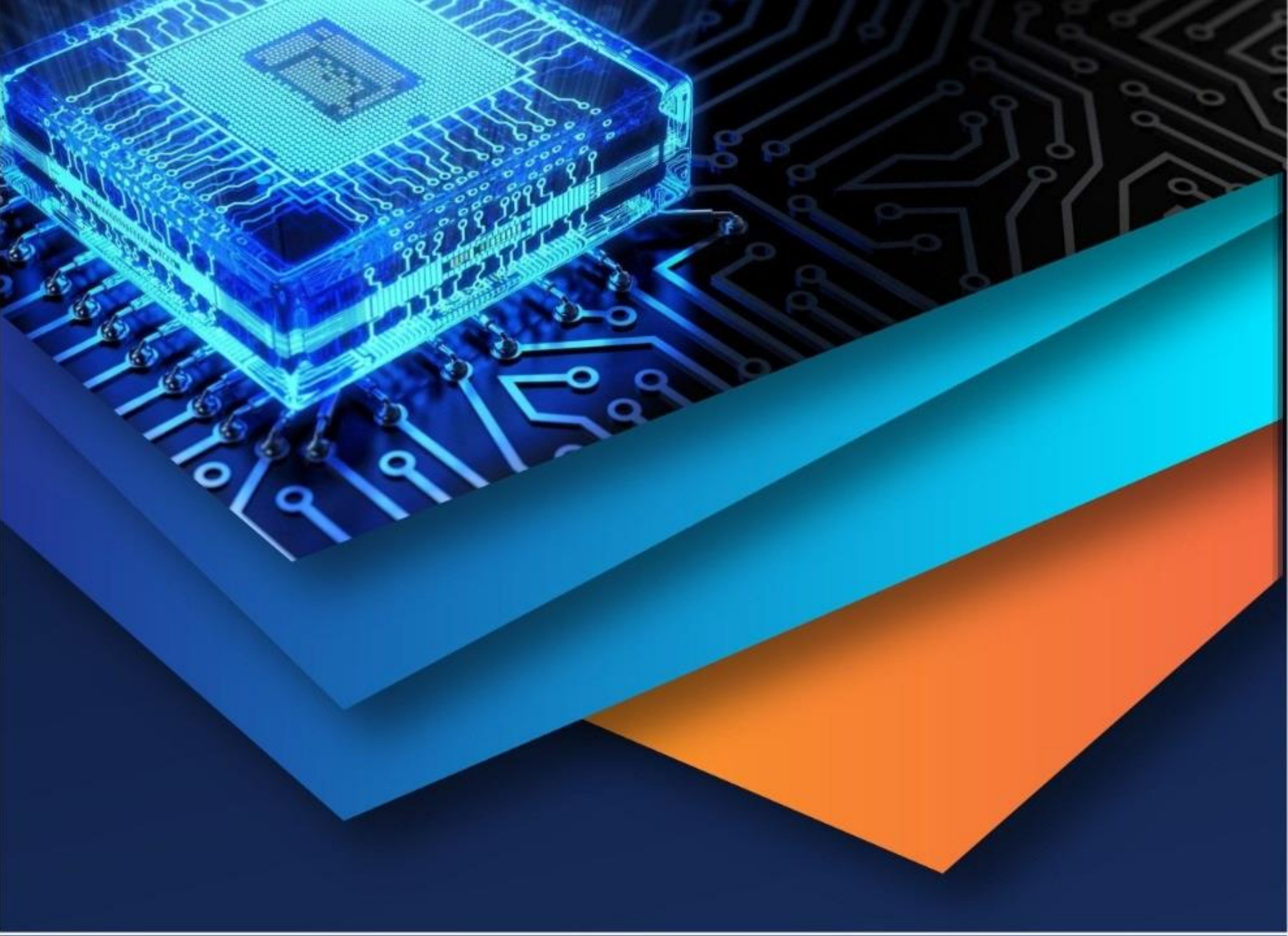
[17] Cham, Marcelo Fernandes Xavier, Radius Tanone, and Hendra Alexan- der T. Riadi. ”Identification of Rice Leaf Disease Using Convolutional Neural Network Based on Android Mobile Platform.” 2021 2nd Interna- tional Conference on Innovative and Creative Information Technology (ICITech). IEEE, 2021

[18] Sathya, R., et al. ”Vision Based Plant Leaf Disease Detection and Recognition Model Using Machine Learning Techniques.” 2023 7th International Conference on Electronic ,Communication and Aerospace Technology (ICECA). IEEE, 2023

[19] Blessy, Y. M., et al. ”Plant disease detection using deep learning and image processing.” Int. J.Electron. Devices Netw 2.2 (2021): 13 16

[20] Meenakshi, T. ”Automatic detection of diseases in leaves of medicinal plants using modified logistic regression algorithm.” Wireless Personal Communications 131.4 (2023): 2573-2597

[21] Martinelli, Federico, et al. ”Advanced methods of plant disease detec- tion. A review.” Agronomy for Sustainable Development 35 (2015)



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