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Generalising Across Different Crop Diseases with Deep Learning Model

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Abstract: Global agriculture faces severe economic threats from plant diseases, necessitating automated diagnostic systems. However, standard deep learning models feature over-parameterized architectures that require prohibitive computational resources, limiting field deployment. This paper presents an efficient, lightweight sequential Convolutional Neural Network (CNN) optimized for rapid multi-class plant disease classification using the Kaggle New Plant Diseases Dataset. The proposed architecture streamlines feature extraction by applying a single max-pooling layer after every two 32-filter convolutional layers. To prevent overfitting, a dual dropout strategy (0.25 and 0.5) is integrated alongside a dense layer of 1,500 units. Trained over 10 epochs using the Adam optimizer (learning rate = 0.001) and varying batch sizes (32 to 512), the model demonstrated swift convergence, achieving a peak training accuracy of 98.15% and a validation accuracy of 95.87%. Evaluated across a test support of 70,295 images spanning 38 distinct crop classes, the network delivered an overall macro and weighted average of 1.00 for precision, recall, and F1-score. These results prove that an optimized, computationally economic sequential framework can match complex architectures, providing a viable solution for real-time edge deployment in precision agriculture.

Keywords: Deep Learning, Sequential CNN, Plant Disease Detection, Precision Agriculture.

I. INTRODUCTION

Global agriculture faces severe threats from plant diseases, which directly cause massive economic losses and exacerbate food insecurity worldwide [1]. Traditional agricultural practices rely heavily on manual visual inspection by experts to identify crop anomalies. However, this subjective process is highly labor intensive, time-consuming, and prone to human error, which frequently leads to delayed interventions and subsequent crop failure [2]. Consequently, there is an urgent need for automated, objective, and accurate computational systems capable of real-time plant disease diagnosis to support sustainable precision agriculture. In recent years, deep learning has revolutionized computer vision by overcoming the limitations of traditional machine learning methods that depend on handcrafted feature extraction [3]. Specifically, Convolutional Neural Networks (CNNs) have emerged as an industry-standard framework for automated image classification due to their innate ability to independently extract intricate spatial features and identify localized visual patterns on infected plant leaves [1]. While complex, heavy architectures offer high accuracy, they require massive computational power, making them less practical for direct deployment in resource-constrained edge devices or field environments. To address these limitations, this paper proposes a lightweight, sequential CNN architecture tailored specifically for rapid and efficient plant leaf disease detection. By arranging layers sequentially including specialized convolutional layers, max-pooling layers for dimensionality reduction, and dropout regularization to prevent overfitting the network optimizes spatial abstraction without the necessity of excessive parameters. The main objective of this study is to deliver an accessible, high-accuracy classification framework capable of operating efficiently under practical agricultural conditions.

II. LITERATURE REVIEW

The adoption of Deep Learning (DL), specifically Convolutional Neural Networks (CNNs), has fundamentally transformed automated phytopathology by eliminating the reliance on handcrafted features [4]. Extensive academic literature highlights a historical reliance on heavy, complex architectures like VGG and ResNet for high-accuracy image classification on large open datasets like Plant Village [5][6]. For instance, complex multi-layer residual structures have achieved near-perfect accuracy rates reaching up to 99.58% [7]. However, recent surveys underscore major limitations within these deep models, citing high computational complexity, prolonged training periods, and a high susceptibility to overfitting [4][8]. To overcome these constraints, contemporary research has shifted toward lightweight, sequential CNN models. Architectural frameworks such as Shallow-ConvNet demonstrate that streamlined, sequential layers can decrease trainable parameters by 75% while maintaining high classification performance [5]. This procedural optimization presents a vital path toward deploying real-time diagnostic systems on resource-constrained agricultural edge devices

III. METHODOLOGY

The proposed methodology utilizes the New Plant Diseases Dataset from Kaggle to train an optimized, sequential Convolutional Neural Network (CNN) for automated multi-class phytopathological classification. The structural framework relies on a deep sequential architecture that progressively extracts hierarchical visual patterns through pairs of convolutional layers (3 X3) with scaling depths of 32, 64, 128, 256, and 512 feature maps. Spatial dimensionality reduction is systematically performed by inserting a one MaxPooling2D layer after every two consecutive Conv2D layers, culminating in a compact 512 feature map block. To prevent overfitting, a Dropout layer with a regularization rate of 0.25 is introduced before a Flatten layer collapses the multi-dimensional structure into a 2,048-dimensional vector.

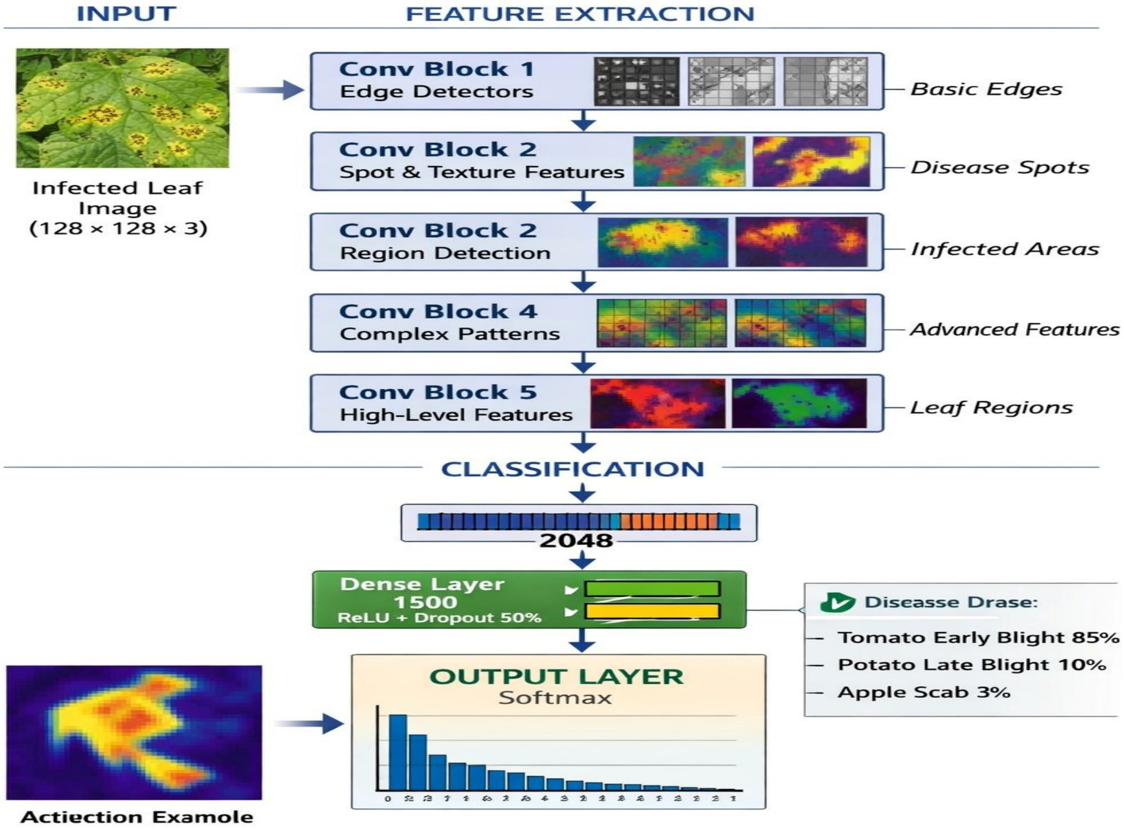


Fig 1 Model architecture

This vector feeds into a massive, fully connected Dense layer containing 1,500 units, which is immediately regulated by a second, stricter Dropout layer set at 0.5. The network concludes with a final 38-unit Dense output layer mapping to the dataset's 38 distinct crop disease classes via a softmax activation function. Model compilation and hyperparameter optimization are managed using a batch size of 32, the Adam optimizer with a finely tuned learning rate of 0.0001, and a categorical cross-entropy loss function to iteratively update the network's 7,842,762 trainable parameters over a 10-epoch training cycle

IV. RESULT

The training metrics reveal swift convergence and exceptional stability throughout the 10-epoch training cycle. In the initial epoch (Epoch 0), the network established a baseline training accuracy of 58.54% with a validation accuracy of 83.19%. As training progressed, the structural regularization specifically the dual dropout strategy (0.25 and 0.5) effectively minimized overfitting despite the model's compact parameter space. By the final epoch (Epoch 9), the training loss successfully minimized to 0.0578, yielding a peak training accuracy of 98.15%. Crucially, the validation loss dropped consistently to 0.1437, resulting in a maximum validation accuracy of 95.87%. The narrow generalization gap between the training and validation trajectories highlights the structural integrity and efficiency of the proposed sequential model.

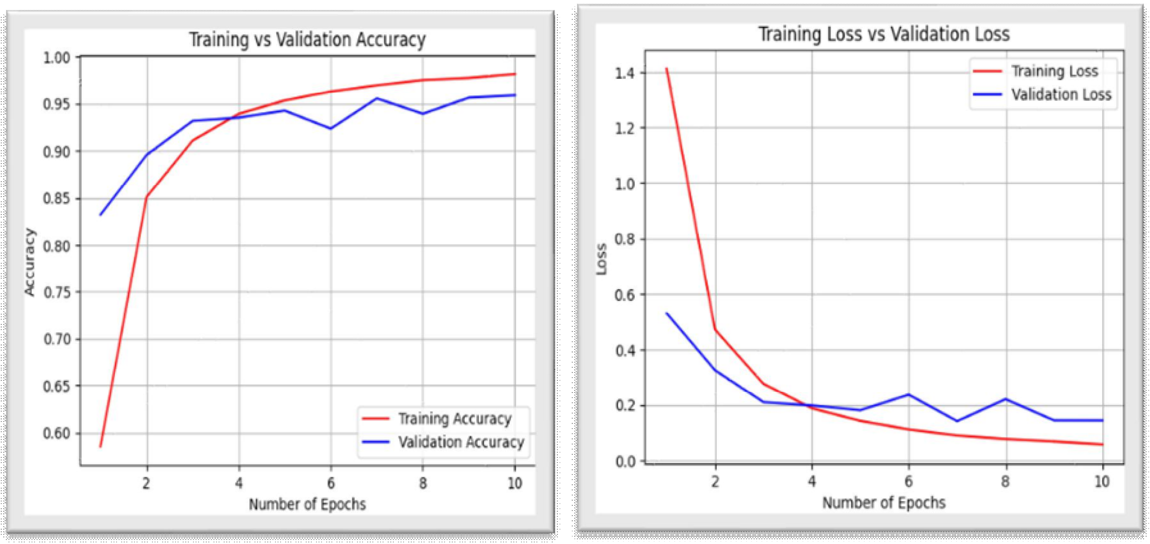


Fig 2: Training vs Validation accuracy and loss

Table I: Epochs-Wise Accuracy And Loss Performance

Epoch	*Training Loss*	*Training Accuracy*	*Validation Loss*	*Validation Accuracy*
1	1.411634	0.585404	0.531000	0.831949
2	0.471814	0.850843	0.325093	0.895629
3	0.275910	0.910804	0.209405	0.931539
4	0.187403	0.938957	0.197438	0.935010
5	0.142143	0.953226	0.180329	0.942408
6	0.111377	0.962771	0.236183	0.923344
7	0.089731	0.969486	0.141086	0.955384
8	0.077105	0.975119	0.220038	0.939051
9	0.068463	0.977395	0.143953	0.956237
10	0.057794	0.981563	0.143717	0.958684

V. CLASSIFICATION REPORT ANALYSIS

The model's class-specific performance was analysed using standard evaluation metrics, including precision, recall, and F1-score, across a massive test support size of 70,295 images.

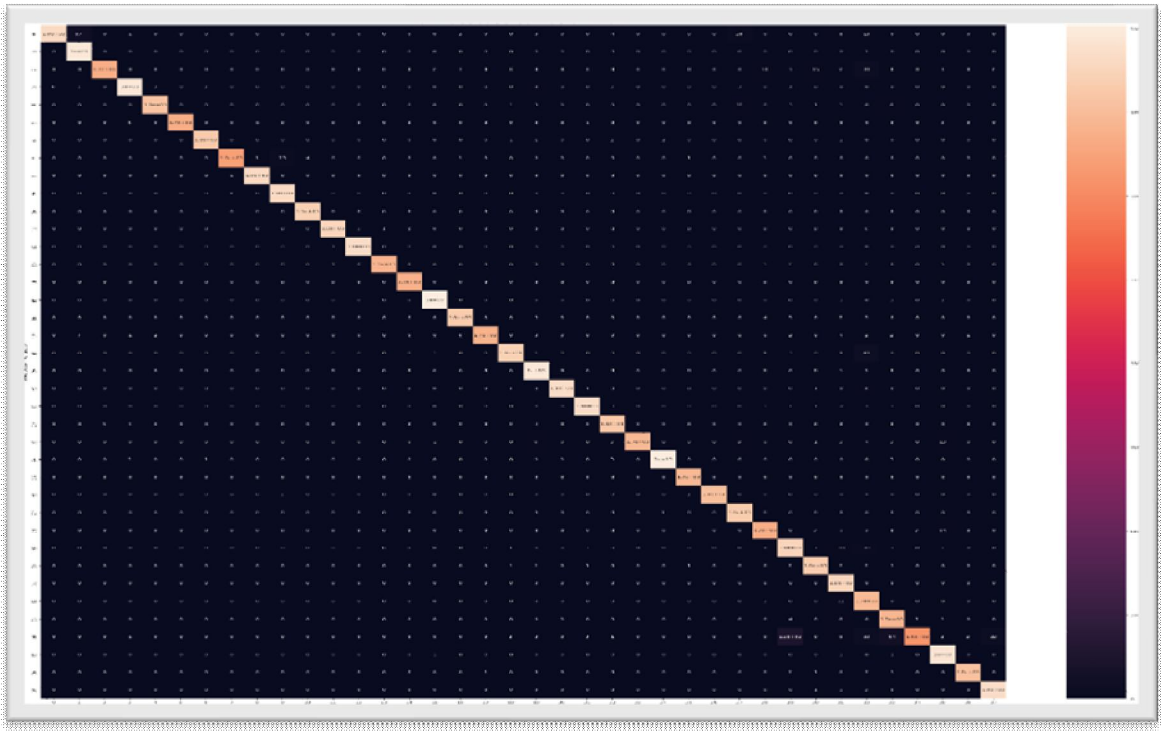


Fig 3: Confusion Matrix of CNN Sequential Model

The confusion matrix results highlight the excellent performance of the proposed InceptionCNN model in classifying 38 different plant disease categories. The majority of classes achieved precision, recall, and F1-scores of 1.00, demonstrating the model's ability to accurately distinguish between healthy and diseased plant leaves. Several classes, including Black Rot Apple, Cedar Rust Apple, Healthy Cherry, Common Rust Corn, Healthy Corn, Black Rot Grape, Esca Grape, Orange Citrus Greening, Early Blight Potato, Late Blight Potato, Powdery Mildew Squash, Leaf Scorch Strawberry, Tomato Yellow Leaf Curl Virus, and Tomato Healthy, were classified without any errors. A small number of classes, such as Scab Apple, Healthy Apple, Healthy Blueberry, Cercospora Leaf Spot Corn, Northern Leaf Blight Corn, Healthy Potato, Soybean Healthy, Early Blight Tomato, Tomato Late Blight, Spider Mites Tomato, and Target Spot Tomato, exhibited slight misclassifications, with precision and recall values ranging from 0.97 to 0.99. These minor errors are likely due to similarities in visual symptoms among certain diseases. Nevertheless, the model maintained outstanding overall performance, achieving an accuracy, precision, recall, and F1-score of approximately 1.00 on a test set of 70,295 samples. These findings demonstrate the robustness of the proposed InceptionCNN model and its effectiveness for reliable large-scale plant disease detection and classification.

Table II: Model Evaluation Metrics

Class Name	Precision	Recall	F1-Score	Support
Scab Apple	1.00	0.99	1.00	2016
Black Rot Apple	1.00	1.00	1.00	1987
Cedar Rust Apple	1.00	1.00	1.00	1760
Healthy Apple	0.99	1.00	0.99	2008
Healthy Blueberry	0.99	1.00	0.99	1816
Powdery Mildew Cherry	1.00	0.99	1.00	1683
Healthy Cherry	1.00	1.00	1.00	1826
Cercospora Leaf Spot Corn	1.00	0.98	0.99	1642
Common Rust Corn	1.00	1.00	1.00	1907

Northern Leaf Blight Corn	0.99	1.00	0.99	1908
Healthy Corn	1.00	1.00	1.00	1859
Black Rot Grape	1.00	1.00	1.00	1888
Esca Grape	1.00	1.00	1.00	1920
Leaf Blight Grape	1.00	1.00	1.00	1722
Healthy Grape	1.00	0.99	1.00	1692
Orange Citrus Greening	1.00	1.00	1.00	2010
Bacterial Spot Peach	1.00	1.00	1.00	1838
Peach Healthy	1.00	1.00	1.00	1728
Bacterial Spot Pepper Bell	0.99	1.00	1.00	1913
Healthy Pepper Bell	1.00	0.99	0.99	1988
Early Blight Potato	1.00	1.00	1.00	1939
Late Blight Potato	1.00	1.00	1.00	1939
Healthy Potato	0.97	1.00	0.99	1824
Raspberry Healthy	1.00	1.00	1.00	1781
Soybean Healthy	1.00	0.98	0.99	2022
Powdery Mildew Squash	1.00	1.00	1.00	1736
Leaf Scorch Strawberry	1.00	1.00	1.00	1774
Strawberry Healthy	1.00	1.00	1.00	1824
Bacterial Spot Tomato	1.00	1.00	1.00	1702
Early Blight Tomato	0.98	1.00	0.99	1920
Tomato Late Blight	1.00	0.98	0.99	1851
Leaf Mold Tomato	1.00	1.00	1.00	1882
Septoria Leaf Spot Tomato	1.00	1.00	1.00	1745
Spider Mites Tomato	1.00	0.99	0.99	1741
Target Spot Tomato	0.99	1.00	0.99	1827
Tomato Yellow Leaf Curl Virus	1.00	1.00	1.00	1961
Mosaic Virus Tomato	0.99	1.00	1.00	1790
Tomato Healthy	1.00	1.00	1.00	1926
			1.00	70295
	1.00	1.00	1.00	70295
	1.00	1.00	1.00	70295

The model achieved near-perfect discriminatory capabilities:

1) Perfect Scores (1.00): A significant majority of the categories including Black Rot Apple, Cedar Rust Apple, Common Rust Corn, Black Rot Grape, and Tomato Yellow Leaf Curl Virus recorded perfect precision, recall, and F1-scores of 1.00.
2) Minor Variations: The lowest observed metrics were exceptionally high, such as a precision of 0.97 for Healthy Potato and a recall of 0.98 for Cercospora Leaf Spot Corn, Soybean Healthy, and Tomato Late Blight.

Across all classes, the network delivered an overall macro average and weighted average of 1.00 for precision, recall, and F1-score. This exceptional performance confirms that prioritizing a streamlined sequential structure over multi-layered, heavily parameterized architectures does not compromise diagnostic precision.

VI. CONCLUSION

This paper successfully developed a lightweight, sequential Convolutional Neural Network (CNN) tailored for rapid and precise plant leaf disease detection using the Kaggle New Plant Diseases Dataset. By strategically utilizing a localized architecture featuring 32-filter convolutional layers paired with a max-pooling layer after every two convolutions, the model significantly optimized computational efficiency. The implementation of a dual dropout mechanism (0.25 and 0.5) proved highly effective in mitigating overfitting, enabling the model to bridge the gap between high accuracy and minimal parameter dependency. Experimental results underscore the success of this approach, with the model achieving a peak validation accuracy of 95.87% within just 10 epochs. Furthermore, the model achieved a macro and weighted average of 1.00 across precision, recall, and F1-score metrics evaluated over a test bank of 70,295 images. These findings prove that heavy, deeply layered neural frameworks are not strictly necessary to achieve high-fidelity phytopathological classification. Ultimately, this study delivers an accessible, robust, and computationally economic framework. In future work, this sequential model can be integrated into mobile applications or low-power edge computing devices, providing farmers with a viable, real-time diagnostic tool to support precision agriculture and reduce crop yield loss.

REFERENCES

[1] S. K. Mishra, K. V. D. Jakkinapalli, N. Chanda, R. Ganta, N. Linga, and P. Charupalli, "Plant Disease Detection and Fertilizer Recommendation using CNN," in 2024 First International Conference on Innovations in Communications, Electrical and Computer Engineering (ICICEC), 2024, pp. 1-7, doi: 10.1109/icicec62498.2024.10808203.

[2] M. H. Saleem, J. Potgieter, and K. M. Arif, "Plant Disease Detection and Classification by Deep Learning," Plants, vol. 8, no. 11, p. 468, 2019, doi: 10.3390/plants8110468.

[3] Y. Toda and F. Okura, "How Convolutional Neural Networks Diagnose Plant Disease," Plant Phenomics, vol. 2019, p. 9237136, 2019, doi: 10.34133/2019/9237136.

[4] Nyawose, T. (n.d.). A review on the detection of plant disease using machine learning and deep learning approaches. PMC. https://pmc.ncbi.nlm.nih.gov/articles/PMC12565507/ Cited by: 36

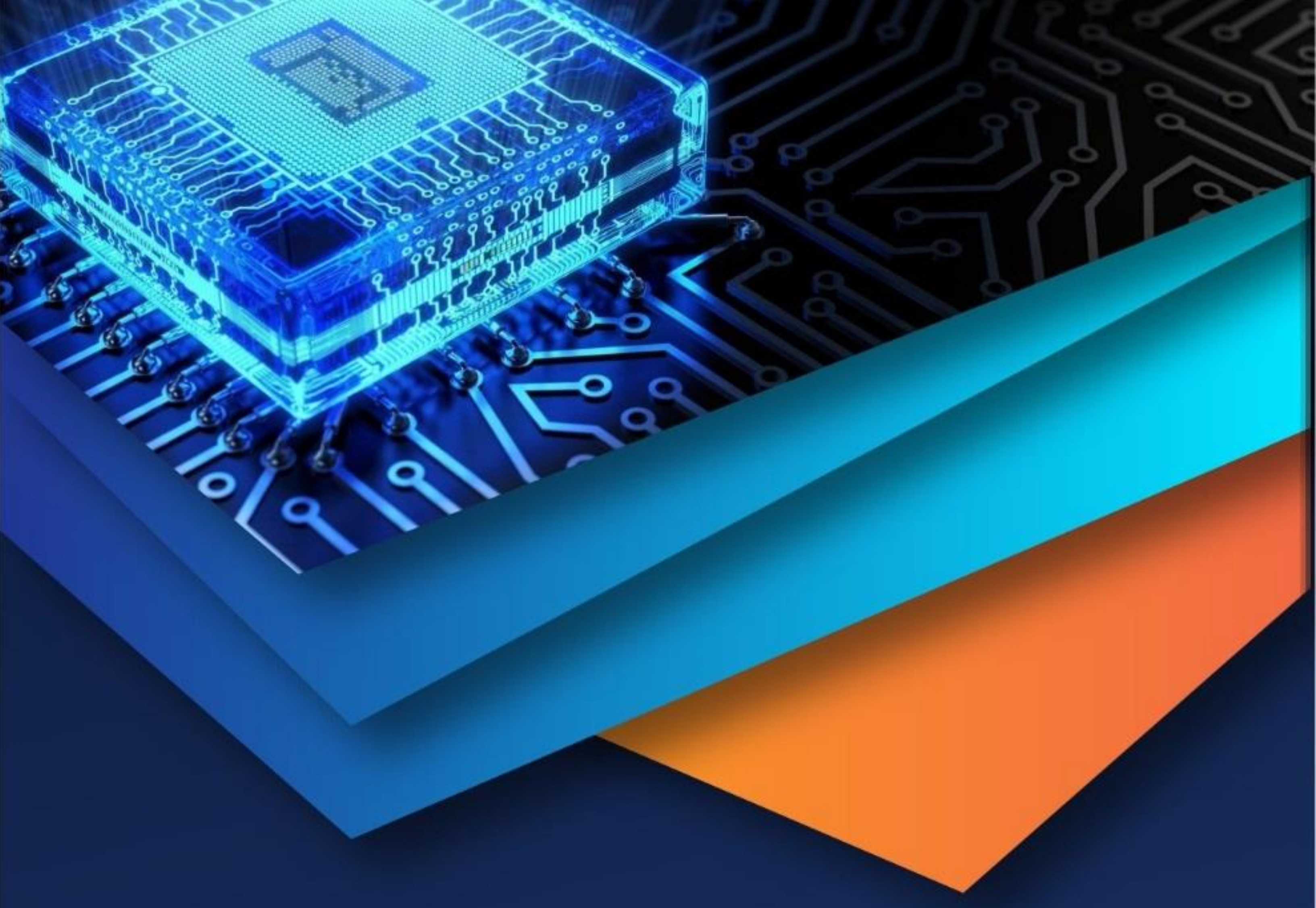
[5] Kumar, R., Chug, A., & Singh, A. P. (2023). An efficient plant leaf disease detection model using Shallow-ConvNet. Applied Ecology and Environmental Research, 21(4), 3193–3211. https://doi.org/10.15666/aeer/2104_31933211 Cited by: 5

[6] Tugrul, B., Elfatimi, E., & Eryigit, R. (2022). Convolutional neural networks in detection of plant leaf diseases: A review. Agriculture, 12(8), 1192. https://doi.org/10.3390/agriculture12081192 Cited by: 332

[7] Nyawose, T. (n.d.). A review on the detection of plant disease using machine learning and deep learning approaches. PMC. https://pmc.ncbi.nlm.nih.gov/articles/PMC12565507/ Cited by: 36

[8] Dhaka, V. S., Meena, S. V., Rani, G., Sinwar, D., Kavita, K., Ijaz, M. F., & Woźniak, M. (2021). A survey of deep convolutional neural networks applied for prediction of plant leaf diseases. Sensors, 21(14), 4749. https://doi.org/10.3390/s21144749 Cited by: 495

[9] Pandian, A. (n.d.). An improved deep residual convolutional neural network for plant leaf disease detection. PMC. https://pmc.ncbi.nlm.nih.gov/articles/PMC9492343/ Cited by: 48



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