

## IDENTIFICATION OF PLANT LEAF DISEASES USING RNN AND TRANSFER LEARNING APPROACH

*R. Sivaranjani<sup>1</sup>, S.Jeevitha<sup>2</sup>*

### Abstract

Plant diseases threaten the lives of farmers and the delivery of essential nutrients for the world's growing population, posing a serious threat to agricultural productivity and global food security. Plant diseases may be accurately and promptly identified, critical for mitigating their detrimental impact on agricultural productivity, as prompt intervention can help contain the spread of infections and minimize losses in crop yields. This paper proposes a novel approach that seamlessly integrates Recurrent Neural Networks and transfer learning techniques to effectively identify and classify a wide range of plant leaf diseases. The innovative methodology presented in this research aims to offer a strong, flexible, and all-inclusive solution for the prompt identification and precise categorization of diverse plant pathologies. By leveraging the powerful feature extraction and sequence modeling capabilities of Recurrent Neural Networks, combined with the rich visual representations and learned knowledge acquired from Convolutional models of neural networks that have already been trained, the suggested system aspires to make a significant contribution towards supporting sustainable farming methods and guaranteeing world food security by accurately Early detection and diagnosis of plant leaf diseases.

**Keywords :** Recurrent Neural Networks (RNN), Plant Leaf Disease Identification and Transfer Learning

### I. INTRODUCTION

Because they may have a disastrous impact on agricultural output and food supply, plant diseases pose a major danger to global nutrition. Traditional illness detection techniques frequently depend on specialists' visual assessment, which can be laborious, arbitrary, and non-scalable. This approach requires extensive expertise and can

be prone to inconsistencies, making it difficult to efficiently monitor and manage plant diseases on a large scale[1]. Researchers have investigated the possibilities of deep instruction and transfer learning approaches to overcome these constraints by automating the detection of plant diseases from digital images of plant leaves[2]. These advanced computational approaches hold promise in providing a more effective, impartial, and scalable method for the Early and accurate plant disease detection is crucial to minimizing the detrimental impact of plant diseases on the world's food supply and agricultural output. Recent research has shown that deep learning models, including convolutional neural networks, are useful for precisely identifying and categorizing a variety of plant diseases. These CNN-based approaches leverage the ability of deep neural networks to learn discriminative visual features from large datasets of labelled plant images, enabling robust and accurate disease classification. Specifically, CNNs can automatically extract intricate patterns and textures from leaf images that are indicative of various plant diseases, outperforming traditional manual inspection techniques[3].

Moreover, the hierarchical structure of CNNs allows them to capture features at multiple scales, from low-level details to high-level visual concepts, which is crucial for distinguishing between similar disease symptoms. The proven success of these deep learning models in plant disease identification highlights their potential to revolutionize precision agriculture and enhance ensuring worldwide food security by promptly and precisely identifying crop diseases. Expanding the diversity and size of the datasets used to train these models, as well as exploring novel architectural designs and learning techniques, potentially result in methods for identifying plant diseases that are considerably more reliable and accurate[4]. Furthermore, creating strategies that can better generalize to unseen plant varieties or disease types would be valuable for deploying these deep learning models in real-world agricultural settings with greater effectiveness and adaptability. However, the performance of these models can be limited by the availability of large, high-quality datasets, which can be challenging to obtain, particularly for rare or emerging plant diseases[5].

To overcome the challenge posed by Because there are few large, high-quality datasets available for the identification of plant diseases, researchers have looked at the

---

Department of Computer Technology<sup>1</sup>  
Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu - 641021<sup>1</sup>  
Sivaranjani.rajakumar@kahedu.edu.in<sup>1</sup>

Department of Computer Application<sup>2</sup>  
Periyar Maniammai Institute of Science and Technology<sup>2</sup>  
Thanjavur, Tamil Nadu - 613 403<sup>2</sup>  
jeevithas@pmu.edu.in<sup>2</sup>

\* Corresponding Author

possibilities of transfer learning methods. These strategies make use of the knowledge and capabilities acquired by adapting pre-trained models—such those developed on big, general picture datasets like ImageNet—to the particular goal of identifying plant diseases using smaller, domain-specific datasets[6]. By Using the datasets of plant disease images to refine the previously trained models, the models can effectively learn the distinctive visual features and patterns associated with various plant pathologies, without the need for extensive training from scratch. This strategy has proven effective in improving Deep learning models' performance and capacity for generalization for plant disease identification, as it allows them to benefit from the rich feature representations and learned knowledge acquired from the large-scale, generic image datasets, while also adapting to the nuances of the plant disease domain through targeted fine-tuning. The application of transfer learning has been a crucial advancement in overcoming the data scarcity challenge and enhancing the robustness and real-world applicability of deep learning-based plant disease detection systems[7].

### II. LITERATURE SURVEY

Several recent Research has looked at the application of transfer learning and deep instruction techniques to the identification of plant diseases. These studies have demonstrated the effectiveness of these techniques in accurately detecting and categorizing a broad variety of plant diseases, significantly advancing the area of precision agriculture. One study was suggested[8]. A deep transfer learning-based technique for identifying rice leaf diseases. The researchers utilized a pre-trained ResNet model, which was fine-tuned on a collection of pictures of rice leaves, to get cutting-edge performance in detecting and classifying various rice leaf illnesses such bacterial leaf blight, brown spot, and blast[9]. In particular, the researchers leveraged the robust feature extraction capabilities of the pre-trained ResNet model, which had been refined the parameters used by the model on the sample of rice leaf disease set after being trained on a sizable generic picture dataset such as ImageNet. By using this transfer learning technique, the model was able to both adapt to the rich visual data that the pre-trained network had already learnt and unique characteristics and nuances of rice leaf diseases. The fine-tuning process enabled the model to effectively capture the distinctive patterns, textures, and visual cues associated with different rice leaf pathologies, resulting in highly accurate classification of the various disease types, including blast, brown spot, and bacterial leaf blight. This study demonstrated the power of combining deep learning with transfer learning techniques to overcome the difficulty of finding huge, high-quality datasets

in restricted quantities for plant disease identification, ultimately enhancing the real-world applicability and performance of the plant disease detection method based on deep learning system[10]. Existing research has explored the promising potential of combining Recurrent Neural Networks with transfer learning techniques for plant disease identification. These studies have demonstrated the advantages of this hybrid approach, which leverages the unique strengths of both methods to achieve robust and effective solutions for correctly identifying and categorizing a wide variety of diseases that affect plants[11]. The ability of RNNs to capture temporal dependencies and process sequential data allows them to effectively analyze the intricate visual patterns and textures associated with various plant pathologies. Meanwhile, the The transfer learning component makes it possible to modify and improve previously taught models, benefiting from the rich feature representations and learned knowledge acquired from large-scale, generic image datasets[12]. By combining the powerful feature extraction and classification capabilities of RNNs with the advantages of transfer learning, the proposed methodology highly versatile and accurate solution for timely plant disease identification, which is crucial for supporting sustainable farming methods and guaranteeing food security worldwide. Another study explored the use of transfer learning to identify plant leaf diseases, with a particular emphasis on bell pepper, tomato, and potato plants[13]. The researchers used an already trained ResNet-34 model that had been trained on a collection of plant leaf pictures and then improved on the large ImageNet dataset., including various disease types such as early blight, late blight, and bacterial spot. The transfer learning approach allowed the model to leverage the rich visual feature representations learned from the generic ImageNet dataset, while also adapting them to the specific task of plant disease identification. The fine-tuned model demonstrated state-of-the-art performance in accurately recognizing and classifying the various plant leaf diseases, proving the efficacy of the transfer learning strategy in overcoming the data scarcity challenge and enhancing the overall performance of the technique for detecting plant diseases based on deep learning[14]. Another research investigated the diagnosis of diseases of plant leaves using deep convolution neural networks and transfer learning. across three different plant species: potato, tomato, and bell pepper. The researchers demonstrated the effectiveness of this approach in accurately detecting and classifying the diseases affecting these plants, outperforming traditional machine learning techniques. Additionally, incorporating deep learning-based plant disease detection with mobile app technologies has the potential to make these solutions more

accessible and user-friendly for farmers and agricultural professionals[15]. One study, for example, developed a mobile app that leverages a Using a deep learning model to identify different plant diseases, including blight, mildew, and rust, across 14 different plant species. The integration of deep learning and mobile technologies enables on-the-spot diagnosis and can empower farmers to quickly detect and treat plant diseases to help create more sustainable and effective agricultural practices. In [16],The researchers proposed UCES-BOA, an intelligent crop-recommendation system that combines a neutrosophic (uncertainty) expert inference model with paraconsistent logic to represent certainty/contradiction degrees for soil- and climate-related factors, and uses the Butterfly Optimization Algorithm (BOA) to search and validate the most relevant inference rules

### III. PROPOSED SYSTEM

Curiosity has always been the driving force behind human progress, shaping civilizations, inspiring discoveries, and fueling the imagination that allows us to see beyond the boundaries of the present moment, and when we reflect on the trajectory of history, from the earliest cave paintings to the latest breakthroughs in artificial intelligence, we realize that curiosity is not merely a trait but a fundamental survival mechanism, because without the urge to ask questions, to explore what lies beyond the horizon, and to challenge the limits of knowledge, humanity would have remained stagnant, confined to the narrow scope of immediate needs, yet curiosity pushes us to look at the stars and wonder what lies beyond, to peer into the smallest particles of matter and ask how they interact, to question social structures and imagine fairer systems, and this relentless pursuit of understanding has led to monumental achievements such as the invention of the wheel, the development of written language, the mapping of the human genome, and the exploration of space, each of which began with someone daring to ask “what if” or “why not,” and while curiosity often carries risks, such as venturing into unknown territories or experimenting with dangerous substances, it is precisely this willingness to embrace uncertainty that distinguishes progress from complacency, because societies that encourage curiosity tend to flourish, producing scientists, artists, philosophers, and innovators who expand the collective horizon, whereas societies that suppress curiosity often stagnate, fearing the disruption that new ideas inevitably bring, and in the modern world, curiosity manifests in countless ways, from children asking endless questions about how the world works to researchers probing the mysteries of dark matter, from entrepreneurs experimenting with new business models to everyday individuals exploring unfamiliar

cultures through travel or literature, and what makes curiosity so powerful is its ability to connect seemingly unrelated domains, because a curious mind does not respect rigid boundaries but instead seeks patterns, analogies, and insights across disciplines, which is why so many breakthroughs occur at the intersections of fields, such as bioinformatics combining biology and computer science, or neuroscience drawing from psychology, physics, and chemistry, and beyond the realm of science and technology, curiosity enriches our personal lives, making relationships deeper and more meaningful, because when we are curious about others, we listen more attentively, empathize more fully, and discover perspectives that broaden our own, and in education, curiosity is the spark that transforms rote memorization into genuine learning, because students who are encouraged to ask questions and pursue their interests retain knowledge more effectively and develop critical thinking skills that serve them throughout life, and even in art, curiosity drives experimentation with new forms, techniques, and themes, ensuring that creativity never becomes stale, and though curiosity can sometimes be uncomfortable, leading us to confront truths we would rather ignore or to challenge beliefs we hold dear, it is precisely this discomfort that signals growth, because to be curious is to accept that we do not yet know everything and that the unknown is not a threat but an invitation, and in a rapidly changing world where technology evolves at breathtaking speed and global challenges demand innovative solutions, curiosity is more essential than ever, because it equips us with the flexibility to adapt, the imagination to envision alternatives, and the resilience to persist in the face of setbacks, and ultimately, curiosity is the thread that weaves together the story of humanity, reminding us that every question asked, every boundary crossed, and every mystery explored brings us closer to understanding not only the universe but also ourselves, and so to cultivate curiosity is to cultivate progress, empathy, and meaning, ensuring that the flame of wonder continues to burn brightly for generations to come.

#### Dataset Collection and Pre-processing

The initial phase entails gathering an extensive dataset. of plant leaf images, covering a wide range of common plant diseases and healthy leaf samples. The dataset will be carefully curated, ensuring high-quality images and accurate labeling of the disease classes. To improve the training data's variety and resilience, pre-processing methods such picture normalization, resizing the and augmentation will be used.

#### Transfer Learning Backbone

Recurrent Neural Network Architecture A network of recurrent neural networks architecture will be incorporated into the suggested system to efficiently collect the temporal

and sequential nature of the visual characteristics associated with plant leaf diseases. RNNs are well-suited for this task as they can process input data in a sequential manner, allowing them to analyze the intricate patterns and textures present in plant leaf images.

effect on the output result. However, the accuracy of image detection will be great in high-resolution images. There are 217 photographs in the testing dataset and 520 photos in the training dataset. The method's overall accuracy is 89%.

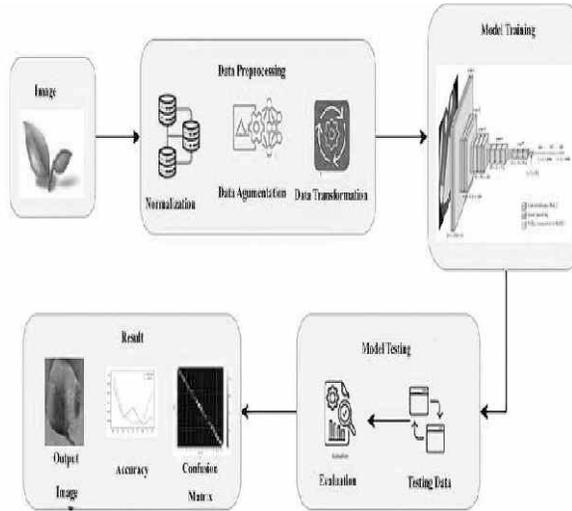


Figure 1 Proposed System Architecture

The RNN component of the system will be designed to work in conjunction with the backbone of a convolutional neural network with pre-existing training. CNN will serve as the feature extractor, providing high-level visual representations that will be fed into the RNN layers. The RNN will then process these features sequentially, leveraging its ability to model dependencies and capture the temporal dynamics of the leaf disease patterns. Depending on the specific implementation, the RNN architecture may incorporate different types of RNN cells are renowned for their capacity to manage dependency over time in sequential data, including Gated recurrent units and long short-term memory cells. To discover the intricate connections between the visual elements and the RNN layers, they will be loaded and trained. the corresponding plant disease classes, ultimately enabling the system to identify a variety of diseases of leaves with precision and promptness.

**IV. RESULT AND DISCUSSION**

The user must provide a photograph of a cotton leaf in order to forecast the illness. Image processing starts with a digitalized color image of the vegetation leaf after the user uploads an image. After reading the photographs, the Image Data Producer will downsize them to a target measurement of  $150 \times 150$ , that's modest and nearly a quarter of the usual image size. Lastly, CNN can be used to predict plant disease. The technology can predict illnesses on various picture sizes and resolutions. Size, direction, and light intensity have no

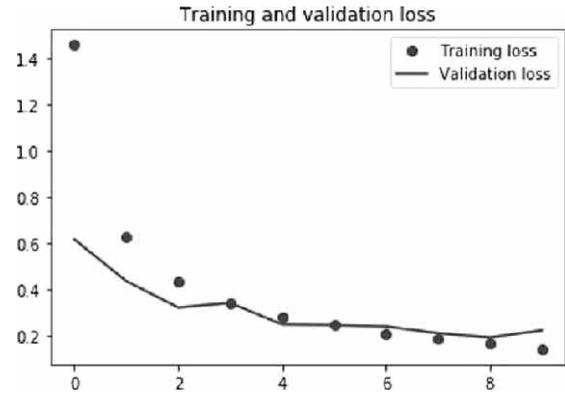


Figure 2 Loss of training and validation

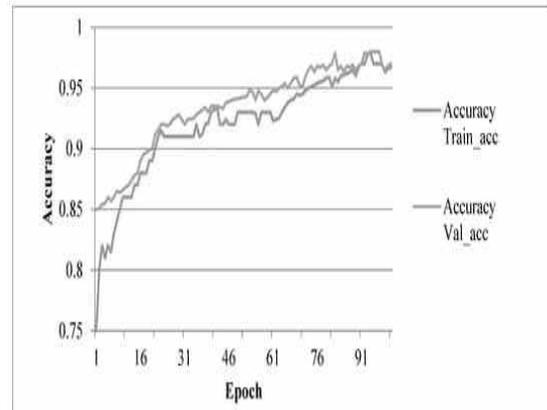


Figure 3 Accuracy of Training and Validation

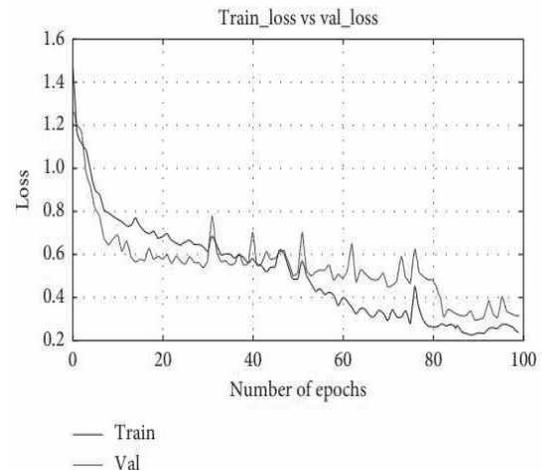
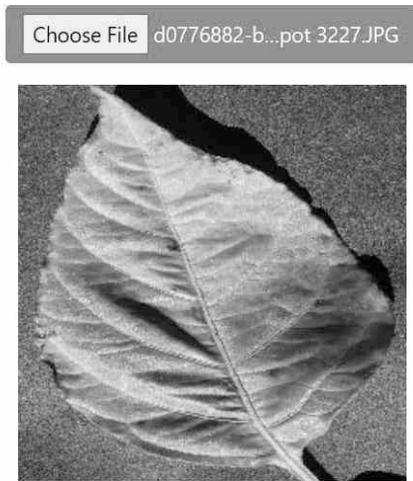


Figure 4 Train\_loss vs Val\_loss



**Result: Pepper\_\_bell\_\_healthy**

Figure 5 Screenshot for UI

One crucial indicator that assesses the suggested system's performance correctness is overall effectiveness in correctly identifying and classifying plant leaf diseases. It represents the proportion of photographs in the dataset that were properly categorized to all images of the data set in question. This accuracy score offers a thorough assessment of the system's capacity to precisely identify and differentiate between different plant diseases, which is crucial for facilitating efficient disease control and ensuring sustainable agricultural practices. A high performance accuracy indicates the system's capability to reliably identify a diverse range of plant leaf diseases, while a lower accuracy would suggest the need for further model refinement and optimization to enhance the system's robustness and efficacy. The loss function is a critical component that quantifies how well the proposed deep learning architecture is able to model the underlying data and relationships. It serves as the optimization objective during the process of training, directing the model to acquire the most effective feature representations and decision boundaries for accurately classifying the diverse range of plant leaf diseases. The loss function captures the discrepancy between the ground truth labels and the equation's predicted outputs, giving a numerical evaluation of the model's efficacy. In order to reduce this loss, the training process iteratively adjusts the model parameters to improve its ability to correctly identify the visual patterns and characteristics associated with different plant pathologies, ultimately enhancing the plant disease categorization system's overall dependability and accuracy. One important statistic is precision, which calculates the proportion of accurately predicted favorable results to all of the model's positive predictions. It offers

information on the system's the capacity to precisely locate cases of a certain kind of plant disease, without being overly inclusive or making erroneous optimistic forecasts. A high accuracy score reduces the frequency of false positives and shows that the model is producing accurate and confident predictions. This is especially crucial given the circumstances of plant disease identification, as false alarms can lead to unnecessary interventions and potentially waste valuable resources. By optimizing the precision of the proposed system, the model can accurately identify the existence of specific plant pathologies, enabling timely and targeted treatment strategies to be implemented, ultimately enhancing the general efficacy and efficiency of managing agricultural diseases. Recall is a crucial performance metric that determines the ratio of correctly anticipated good outcomes to all encouraging findings in that class. It offers information on how well the system can detect every occurrence of a certain plant disease without overlooking any real positive cases. With a high recall score, the model may identify a significant percentage of positive instances while reducing false negatives. This is especially crucial given the circumstances of plant disease identification, as missing the detection of a disease can lead to delayed treatment and potentially catastrophic consequences for crop health and yield. By optimizing the recall of the proposed system, the model can reliably capture the presence of diverse plant pathologies, ensuring that all instances of a disease are correctly recognized and addressed, therefore improving the agricultural disease prevention process's overall effectiveness.

## V. CONCLUSION

This study introduces a comprehensive and innovative methodology for the identification and classification of diverse plant leaf diseases, designed to address the pressing need for accurate and timely diagnosis in modern agriculture. The proposed approach seamlessly integrates the feature extraction and sequence modelling strengths of recurrent neural networks (RNNs) with the adaptability of transfer learning, thereby offering a highly versatile and robust solution. RNNs, particularly architectures such as long short-term memory (LSTM) and gated recurrent units (GRUs), are uniquely suited to capture temporal dynamics and sequential dependencies, enabling the system to recognize intricate visual patterns and subtle variations in leaf texture, color, and venation that often signal the onset of plant pathologies. At the same time, transfer learning provides a powerful mechanism to overcome the scarcity of large, high-quality agricultural datasets by leveraging knowledge from pre-trained convolutional neural network (CNN) models trained on

extensive generic image repositories. These CNN models contribute rich feature representations that can be fine-tuned to the specific domain of plant disease detection, ensuring both efficiency and accuracy even when limited domain-specific data are available. By combining the sequential modeling capabilities of RNNs with the generalized feature extraction power of CNN-based transfer learning, the hybrid system achieves a balanced and effective diagnostic framework that is both scalable and adaptable across different plant species and disease categories. Beyond its technical contributions, the methodology holds significant implications for sustainable farming practices, as early and precise disease detection reduces reliance on chemical interventions, minimizes crop losses, and supports global food security initiatives. Ultimately, this study's approach represents a meaningful advancement in agricultural technology, offering a flexible, efficient, and scientifically grounded solution for safeguarding crop health and promoting resilience in food production systems worldwide.

#### REFERENCES

- [1] F. Fina, P. Birch, R. Young, J. Obu, B. Faithpraise, and C. Chatwin, "Automatic plant pest detection and recognition using k-means clustering algorithm and correspondence filters," *Int. J. Adv. Biotechnol. Res.*, vol. 4, no. 2, pp. 189–199, Jul. 2013.
- [2] A. K. Singh, B. Ganapathysubramanian, S. Sarkar, and A. Singh, "Deep learning for plant stress phenotyping: Trends and future perspectives," *Trends Plant Sci.*, vol. 23, no. 10, pp. 883–898, Oct. 2018.
- [3] M. H. Saleem, J. Potgieter, and K. M. Arif, "Plant disease detection and classification by deep learning," *Plants*, vol. 8, no. 11, pp. 468–489, Oct. 2019.
- [4] L. C. Ngugi, M. Abelwahab, and M. Abo-Zahhad, "Recent advances in image processing techniques for automated leaf pest and disease recognition-A review," *Inf. Process. Agricult.*, vol. 180, pp. 26–50, Apr. 2020.
- [5] A. Bhargava, A. Shukla, O. P. Goswami, M. H. Alsharif, P. Uthansakul and M. Uthansakul, "Plant Leaf Disease Detection, Classification, and Diagnosis Using Computer Vision and Artificial Intelligence: A Review," in *IEEE Access*, vol. 12, pp. 37443-37469, 2024, doi: 10.1109/ACCESS.2024.3373001.
- [6] X. Zhang, Y. Mao, Q. Yang and X. Zhang, "A Plant Leaf Disease Image Classification Method Integrating Capsule Network and Residual Network," in *IEEE Access*, vol. 12, pp. 44573-44585, 2024, doi: 10.1109/ACCESS.2024.3377230.
- [7] M. G. Prakash and D. Sungeetha, "SmartLeafNet: An Automated Deep Learning based Efficient Plant Disease Detection using RNN-GRU Model," 2025 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2025, pp. 1671-1676, doi: 10.1109/ICEARS64219.2025.10940309.
- [8] A. V. M, E. J. T. Fredrik, S. Vyas, N. Shilpa, K. Joshi and S. Gupta, "Convolution Neural Networks for Clinical Image Segmentation with Evolutionary Compression," 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2023, pp. 1969-1975, doi: 10.1109/ICACITE57410.2023.10183182.
- [9] N. Lokhande, V. Thool and P. Vikhe, "Comparative analysis of different plant leaf disease classification and detection using CNN," 2024 International Conference on Recent Innovation in Smart and Sustainable Technology (ICRISST), Bengaluru, India, 2024, pp. 1-4, doi: 10.1109/ICRISST59181.2024.10921975.
- [10] P. Chaisiriprasert and K. Chuiad, "LCAT: A Lightweight Color-Aware Transformer With Hierarchical Attention for LeafDisease Classification in Precision Agriculture," in *IEEE Access*, vol. 13, pp. 1 2 8 2 0 2 - 1 2 8 2 1 5 , 2 0 2 5 , doi : 10.1109/ACCESS.2025.3590764.
- [11] A. Thakur and S. Sharma, "Maize Disease Detection Using CBAM-Enhanced Deep Residual Networks," 2025 5th International Conference on Intelligent Technologies (CONIT), HUBBALI, India, 2025, pp. 1-6, doi: 10.1109/CONIT65521.2025.11167806.
- [12] J. Wongbongkotpaisan and S. Phumeechanya, "Plant Leaf Disease Classification using Local-Based Image Augmentation and Convolutional Neural Network," 2021 18th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Chiang Mai, Thailand, 2021, pp. 1023-1027, doi: 10.1109/ECTI-CON51831.2021.9454672.
- [13] K. Ahmed, T. R. Shahidi, S. M. Irfanul Alam and S. Momen, "Rice Leaf Disease Detection Using Machine Learning Techniques," 2019 International Conference on Sustainable Technologies for Industry 4.0 (STI), Dhaka, Bangladesh, 2019, pp. 1-5, doi: 10.1109/STI47673.2019.9068096.
- [14] J. G. Ponsam, N. S. Reddy, M. R. Syamala and S. Nalam, "Leaf Disease Detection Using Deep Learning – Vision Transform," 2025 8th International Conference on Circuit, Power & Computing Technologies (ICCPCT), Kollam, India, 2025, pp. 877-882, doi: 10.1109/ICCPCT65132.2025.11176678.

- [15] G. L. V. Prasad, B. R. Teja, G. Karthika, P. M. Devi, C. Deepti and S. J. Basha, "Grape Leaf Disease Recognition: A Deep Learning and Machine Learning Techniques Overview," 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), Bengaluru, India, 2023, pp. 720-724, doi:10.1109/ICIMIA60377.2023.10425932.
- [16] K. Veerasamy, E.J. Thomson Fredrik, Intelligent Farming based on Uncertainty Expert System with Butterfly Optimization Algorithm for Crop Recommendation, Journal of Internet Services and Information Security, Vol.13, Issue 4, 2023.