



Hybrid CNN-LSTM Techniques for Plant Leaf Disease Detection and Farmer-Based Agricultural Practice Analysis in Western Tamil Nadu

Valarmathi Palaniappan^{1*}, and Laurence Aroquiaraj²

¹ Research Scholar (Part Time), Department of Computer Science, Periyar University, Salem, India
Department of Computer Science and Applications, Vivekanandha College of Arts and Sciences for Women (Autonomous),
Affiliated to Periyar University, Namakkal DT, India

² Department of Computer Science, Periyar University, Salem, India

* Correspondence: mathijaga04@gmail.com

Citation:

Valarmathi P.; Laurence Aroquiaraj, I.; Hybrid CNN-LSTM techniques for plant leaf disease detection and farmer-based agricultural practice analysis in western tamil nadu. *ASEAN J. Sci. Tech. Report.* **2026**, 29(11), e262967. <https://doi.org/10.55164/ajstr.v29i11.262967>

Article history:

Received: December 24, 2025

Revised: June 10, 2026

Accepted: June 13, 2026

Available online: October 11, 2026

Publisher's Note:

This article is published and distributed under the terms of the Thaksin University.

Abstract: Plant diseases greatly affect crop productivity and agricultural sustainability, making early and accurate disease detection essential. This study investigates hybrid deep learning techniques for plant leaf disease detection and classification, focusing on combining Convolutional Neural Networks and Long Short-Term Memory networks. A review of existing studies revealed that the CNN-LSTM hybrid model achieved over 98% accuracy, outperforming several other hybrid approaches. In addition, a survey of 140 farmers from the western districts of Tamil Nadu analyzed farming practices, disease identification methods, and management techniques. The findings indicate that younger farmers are gradually adopting modern agricultural technologies, while older farmers continue to rely on traditional practices. The study highlights the effectiveness of CNN-LSTM models for smart agriculture and emphasizes the importance of farmer awareness and technology adoption for sustainable crop management.

Keywords: CNN; LSTM; plant disease detection; plant disease prevention; plant leaf classification

1. Introduction

Agriculture plays a vital role in global food security and economic sustainability, particularly in countries like India, where it contributes about 10% to the GDP and supports nearly 70% of the population. However, plant diseases significantly impact crop yield and quality, posing a serious challenge to food production systems. For crops such as tomatoes, which are both economically important and nutritionally rich, disease management is critical for maintaining productivity and profitability. Diseases such as early blight, late blight, powdery mildew, and bacterial wilt can cause substantial yield losses, estimated at 10% to 20% annually in India. These diseases often arise from factors such as climatic conditions, insect activity, and environmental pollutants. Early and accurate disease detection is essential to minimize losses and ensure sustainable crop management. Traditionally, plant disease identification has relied on visual inspections conducted by experienced technicians or agricultural scientists. This appearance-based diagnosis involves observing changes in the color, shape, and growth rates of plant parts.

However, this method is time-consuming, labor-intensive, and subject to human error, particularly where farmers lack formal training. In recent years, smart agriculture has emerged as a solution to many of these challenges. It leverages modern information technologies, including the Internet of Things (IoT) and Artificial Intelligence (AI), to enhance decision-making in crop management. One key area is leaf disease detection and classification, which is considered both challenging and crucial for precision agriculture.

Among AI methods, image classification plays a central role in identifying whether a plant leaf is infected or healthy. Convolutional Neural Networks (CNNs) have become popular in this domain because they can automatically extract hierarchical features from images. CNNs have shown strong performance in classifying diseases in various crops, including fruits and vegetables, based on leaf image datasets. Moreover, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, enhance temporal feature learning by remembering patterns over longer sequences. When combined with CNNs in a hybrid architecture, LSTMs can improve detection by modeling temporal dependencies, such as the progression of disease symptoms over time. This CNN-LSTM hybrid model is particularly effective at analyzing complex patterns in leaf images for early, accurate disease diagnosis. CNNs handle spatial feature extraction, while LSTMs learn temporal patterns in sequential data, making the system capable of both classification and prediction of disease outbreaks. Such systems enable timely interventions, whether through targeted pesticide application or isolation of infected plants, thereby reducing economic losses and improving crop health.

With advances in computer vision, farmers and agricultural systems can now use smartphones or digital cameras to capture leaf images, which are preprocessed (e.g., resized, normalized, and augmented) to build robust datasets for model training. These technologies offer scalable, cost-effective, real-time solutions for disease detection, particularly in resource-constrained environments. Furthermore, integrating deep learning in agriculture enhances crop management strategies, leading to higher yields, improved food quality, and greater resilience against plant diseases. It marks a significant step toward sustainable agriculture and helps secure the future of food production. The objective of the paper to compare hybrid deep learning techniques for plant leaf disease detection and classification and identify the most effective model for accurate disease prediction in smart agriculture, design a questionnaire to collect information from farmers regarding their cultivation practices and how they identify and manage plant diseases, including prevention methods, data were collected from western TamilNadu districts such as Namakkal, Salem, Dharmapuri, and Tiruppur, and analyzed using two-dimensional percentage analysis, critical analysis, and Regression Analysis.

2. Materials and Methods

2.1 Research model

To achieve the objective of the research article, the designed questionnaire has been classified into four divisions: (i) Socio-Profile of the Farmers, (ii) Farmers' Family and their Property Classification, (iii) Farmers' Agricultural Practices, and (iv) Plant Cultivation and Management. Age, experience, and practice method – whether full-time or part-time participation – are included in the first division: socio-profile of the farmers. The second division includes family type, number of family members, family participation, property type, and land area. The farmers' agricultural practices division includes plant cultivation type, disease identification methods, and preventive and management practices. The plant cultivation and management division includes plant types and management techniques.

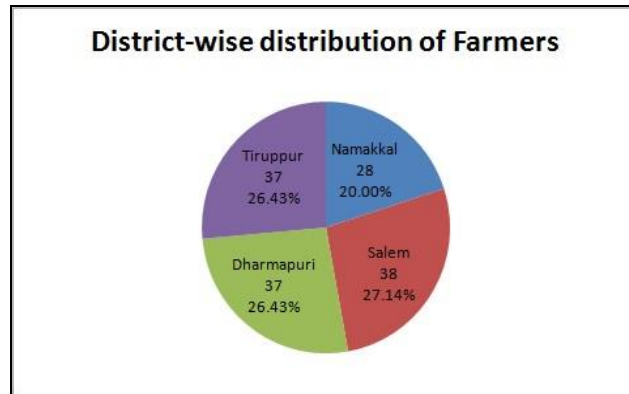


Figure 1. District-wise distribution of Farmers

The questionnaire was validated using content validation with a 4-point scale (Not relevant, Relevant, Satisfactory, Highly relevant), and a pilot test was conducted with 30 respondents. To achieve the third objective of the paper, data were collected from 170 farmers in the western districts of Tamil Nadu, namely Namakkal, Salem, Dharmapuri, and Tiruppur, using a convenience sampling method. After data cleaning, 140 respondents were selected based on availability; farmers were selected as follows: Namakkal district (28 farmers, i.e., 20.00%), Salem district (38 farmers, i.e., 27.14%), Dharmapuri district (37 farmers, i.e., 26.43%), and Tiruppur district (37 farmers, i.e., 26.43%). The data were analyzed using two-dimensional percentage analyses. All questionnaire variables were included in the percentage analysis, and the first division under the second objective was analyzed in relation to the other three divisions using linear regression analysis. Finally, the variables were subjected to a correlation matrix and critical analysis to arrive at a clear and detailed conclusion.

2.2 Proposed Work

To achieve the objectives of this paper, approximately 22 articles were collected from existing research published in reputable, peer-reviewed journals. These studies focused on Plant disease classification, Plant leaf disease detection, and prevention using hybrid techniques such as CNN combined with RNN, LSTM, VGG16, Decision Tree, kNN, and others. The selected articles were studied and analyzed with respect to the techniques used, datasets employed, and results achieved. Table 1 presents the consolidated details. The analysis identified that CNN vs. HBOA, CNN vs. LSTM, and CNN vs. RNN achieved 99.58%, 98.65%, and 98.25%, respectively, for Plant disease detection. For Plant leaf disease classification, the combinations CNN vs LDI-NET, CNN vs LSTM, and CNN vs RNN achieved accuracy rates of 99.42%, 98.17%, and 91.00%, respectively.

Table 1. Hybrid techniques for Plant disease classification, leaf disease detection and prevention

S. No	Reference	Hybrid Algorithms	Purpose	Accuracy
1	Sameera &Abhay Deshpande	CNN Vs HBOA	Disease detection	99.58%
2	BinYang et.al	CNN Vs LDI-NET	Classification	99.42%
3	Vasumathi & Kamarasan	CNN Vs LSTM	Disease detection	98.65%
4	Aryan Chaudhary et.al	CNN Vs LSTM	Disease detection	98.40%
5	Hepzibah Elizabeth David et.al	CNN Vs RNN	Disease detection	98.25%
6	Vasumathi & Kamarasan	CNN Vs LSTM	Classification	98.17%
7	Hukkeri et.al	CNN Vs VGG16	Disease detection	97.50%
8	Hukkeri et.al	CNN Vs Efficient-Net	Disease detection	97.50%
9	Le et.al	CNN Vs RNN	Disease detection	97.15%
10	Salini et.al	CNN Vs LSTM	Disease detection	95.41%
11	Rama Chandran et.al	CNN Vs LSTM	Disease detection	95.33%
12	Shwetha et.al	CNN Vs Decision tree	Classification	94.00%
13	Khaki et.al	CNN Vs RNN	Disease detection	92.00%
14	Khaki et.al	CNN Vs RNN	Classification	91.00%

Table 1. Hybrid techniques for Plant disease classification, leaf disease detection and prevention (continue)

S. No	Reference	Hybrid Algorithms	Purpose	Accuracy
15	BinYang et.al	CNN Vs LDI-NET	Disease detection	88.55%
16	Fubing Liao et.al	ResNet10 Vs LSTM	Classification	88.38%
17	Fubing Liao et.al	ResNet10 Vs SE	Classification	85.88%
18	Shwetha et.al	CNN Vs kNN	Classification	85.00%
19	Hepzibah Elizabeth David et.al	CNN Vs RNN	Classification	81.75%

3. Results and Discussion

3.1 Two-Dimensional Percentage Analysis of the Socio-Economic Profile of the Farmers

To achieve the second objective of the first division and the third objective, the socio-economic profile of the farmers was analyzed using a two-dimensional percentage analysis. In this analysis, the first dimension represents the classification of variables, while the second dimension reflects the district-wise classification. Table 2 illustrates the district-wise classification of the socio-economic profile of the farmers. According to Table 2, 37 farmers belonged to the 30-40 Years age group, 34 farmers to the 40-50 Years age group, 33 farmers to the 50-60 Years age group, and 36 farmers were above 60 Years of age. Specifically, the highest number of farmers (10) in Namakkal district belonged to the 50-60 Years age group; in Salem and Tiruppur districts, the highest number of farmers (13 each) were in the 30-40 Years age group; and in Dharmapuri district, the highest number of farmers (12) were above 60 Years of age. While analyzing the farmers' experience, 38, 33, 41, and 28 farmers have 10 years, 20 years, 30 years, and more than 30 years of experience, respectively. Dharmapuri has the highest number of farmers with 30 years of experience (14 farmers), followed by Tiruppur, which has the highest number of farmers with 10 years of experience (13 farmers). While analyzing the farmers' practices, 66 and 74 farmers are engaged in full-time and part-time work, respectively. It was found that 52.86% of farmers engage in agriculture as part-time work. In Salem district, the highest number of farmers (23, i.e., 60.53% of 38 farmers) work part-time.

Table 2. District-wise classification of the socio profile of farmers

S. No	Variables	Classification	Districts				Total No. of Farmers with Percentage
			Namakkal	Salem	Dharmapuri	Tiruppur	
1	Age	30-40	6 (21.43%)	13 (34.21%)	5 (13.51%)	13 (35.14%)	37 (26.43%)
		40-50	7 (25.00%)	9 (23.68%)	10 (27.03%)	8 (21.62%)	34 (24.29%)
		50-60	10 (35.71%)	6 (15.79%)	10 (27.03%)	7 (18.92%)	33 (23.57%)
		Above 60	5 (17.86%)	10 (26.32%)	12 (32.43%)	9 (24.32%)	36 (25.71%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					
2	Experience	10 Years	6 (21.43%)	8 (21.05%)	11 (29.73%)	13 (35.14%)	38 (27.14%)
		20 Years	9 (32.14%)	9 (23.68%)	7 (18.92%)	8 (21.62%)	33 (23.57%)
		30 Years	6 (21.43%)	11 (28.95%)	14 (37.84%)	10 (27.03%)	41 (29.29%)
		Above 30	7 (25.00%)	10 (26.32%)	5 (13.51%)	6 (16.22%)	28 (20.00%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					
3	Practice Method	Full Time	14 (50.00%)	15 (39.47%)	20 (54.05%)	17 (45.95%)	66 (47.14%)
		Part Time	14 (50.00%)	23 (60.53%)	17 (45.95%)	20 (54.05%)	74 (52.86%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					

3.2 Two-Dimensional Percentage Analyses of Farmers' Families and their Property Classification

To achieve the second objective of the second division and the third objective, the classification of farmers' families and their property was analyzed using a two-dimensional percentage analysis. In this division, family type, number of family members, family participation in farming, property type, and land area were analyzed, and the results are presented in Table 3. Table 3 shows that 72 farmers (i.e., 51.43% of 140) belong to single (nuclear) families, while 68 belong to joint families. Based on district-wise analysis, the highest number of farmers living in single families was in Dharmapuri district-23 farmers (i.e., 62.16% of 37). This was followed by Salem district, where 22 farmers (57.89% of 38) live in single families. In contrast, 59.46% of farmers in Tiruppur district live in joint families.

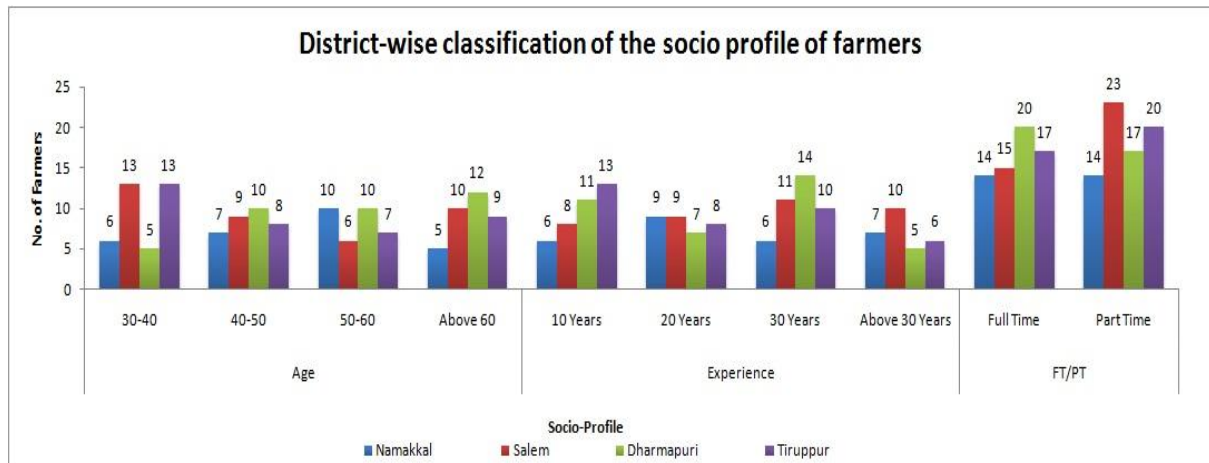


Figure 2. District-wise classification of the socio profile of farmers

Analysis of family size showed that the highest number, 38 families (27.14% of 140), had 9 to 12 members. This was followed by 35 families (25.00% of 140) with 3 to 5 members. A district-wise analysis revealed that in Tiruppur district, the highest number, 13 families (35.14% of 37), had 3 to 5 members. In Salem district, the highest number, 12 families (31.58% of 38), had 6 to 8 members. Analysis of family participation in agriculture found that 68 families (48.57% of 140) were fully engaged in farming. The remaining 72 families (51.43% of 140) were only partially engaged in agricultural activities. A district-wise analysis showed that in Tiruppur district, the majority, 26 families (70.27% of 37), were partially engaged in farming. In contrast, in Salem district, the majority, 25 families (67.79% of 38), were fully engaged in agricultural work.

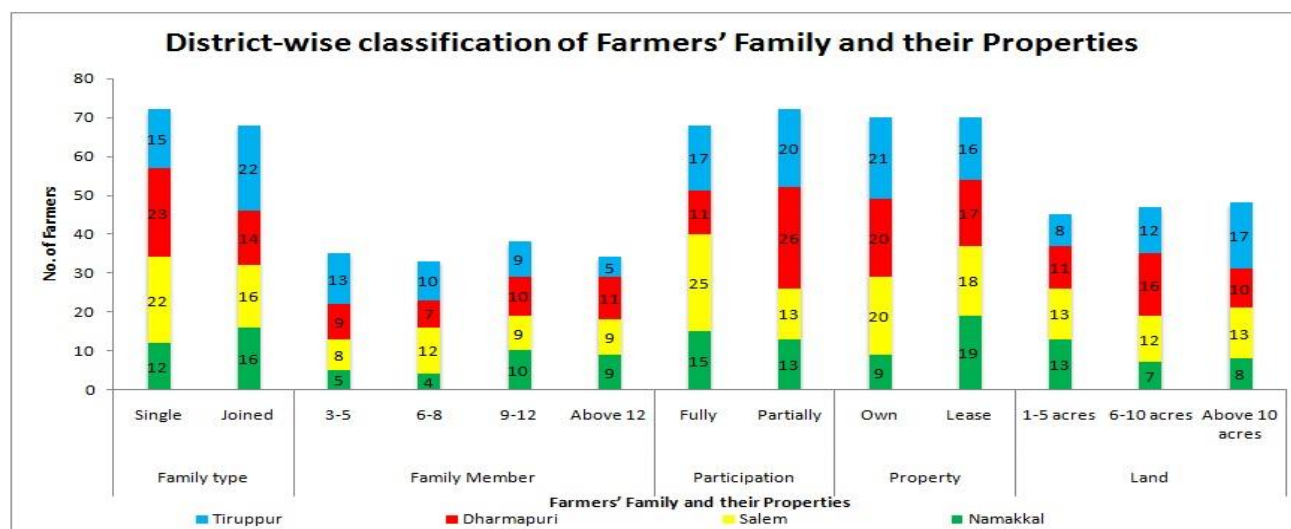


Figure 3. District-wise classification of Farmers' Family and their Properties

Analysis of farmers' property types showed that 70 farmers (50.00% of 140) own their property, while the remaining 70 farmers (50.00% of 140) lease their property. In Tiruppur district, the highest number of farmers, 21 (56.76% of 37), own their property. This was followed by 20 farmers (52.63% of 38) in Salem district who own their property, and 54.05% of farmers (37 farmers) in Dharmapuri district who own their property. While analyzing land area, it was found that the highest number of farmers, 48 (34.29% of 140), have more than 10 acres of Land for farming. The next highest, 47 farmers (33.57% of 140), have 6 to 10 acres of land. In district-wise analysis, the highest number of farmers in the district, 17 (45.95% of 37), have more than 10 acres of land for farming. In Dharmapuri district, 16 farmers (43.24% of 37) have between 6 to 10 acres of land for farming. Figure 3 presents the overall district-wise classification of farmers' families and their property.

Table 3. District-wise classification of Farmers' Family and their Properties

S. No	Variables	Classification	Districts				Total No. of Farmers with Percentage
			Namakkal	Salem	Dharmapuri	Tiruppur	
1	Family Type	Single	12 (42.86%)	22 (57.89%)	23 (62.16%)	15 (40.54%)	72 (51.43%)
		Joined	16 (57.14%)	16 (42.11%)	14 (37.84%)	22 (59.46%)	68 (48.57%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					
2	No. of Family Members	3-5	5 (17.86%)	8 (21.05%)	9 (24.32%)	13 (35.14%)	35 (25.00%)
		6-8	4 (14.29%)	12 (31.58%)	7 (18.92%)	10 (27.03%)	33 (23.57%)
		9-12	10 (35.71%)	9 (23.68%)	10 (27.03%)	9 (24.32%)	38 (27.14%)
		Above 12	9 (32.14%)	9 (23.68%)	11 (29.73%)	5 (13.51%)	34 (24.29%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
3	Family Participation	Fully	15 (53.57%)	25 (65.79%)	11 (29.73%)	17 (45.95%)	68 (48.57%)
		Partially	13 (46.43%)	13 (34.21%)	26 (70.27%)	20 (54.05%)	72 (51.43%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					
4	Property Type	Own	9 (32.14%)	20 (52.63%)	20 (54.05%)	21 (56.76%)	70 (50.00%)
		Lease	19 (67.86%)	18 (47.37%)	17 (45.95%)	16 (43.24%)	70 (50.00%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					
5	Area of Land	1-5 acres	13 (46.43%)	13 (34.21%)	11 (29.73%)	8 (21.62%)	45 (32.14%)
		6-10 acres	7 (25.00%)	12 (31.58%)	16 (43.24%)	12 (32.43%)	47 (33.57%)
		Above 10 acres	8 (28.57%)	13 (34.21%)	10 (27.03%)	17 (45.95%)	48 (34.29%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					

3.3 Two-Dimensional Percentage Analyses of Farmers' Agricultural Practices

To achieve the second objective of the third division and the third objective, Farmers' Agricultural Practices were classified and analyzed using a two-dimensional percentage analysis. In this division, plant cultivation type, disease identification methods, preventive practices, and management practices were analyzed, and the results are presented in Table 4. Table 4 shows that 67 farmers (47.86% of 140) cultivate

single plants, while 73 farmers (52.14% of 140) cultivate multiple plants. Based on district-wise analysis, Dharmapuri district had the highest number of farmers cultivating multiple plants, with 28 farmers (75.68% of 37). In contrast, 23 farmers in Salem district (60.53% of 38) and 23 farmers in Tiruppur district (62.16% of 37) were cultivating a single plant. Analysis of the disease identification methods used by farmers found that 72 farmers (51.43% of 140) identified diseases on their own, while the remaining 68 farmers (48.57% of 140) relied on others, such as agricultural laboratory officials and senior farmers living nearby. Based on the district-wise analysis, 20 farmers (54.05% of 37) in Tiruppur district identified diseases on their own. In contrast, 20 farmers (54.05% of 37) in Dharmapuri district identified diseases with the help of others.

Table 4. District-wise classification of Farmers' Agricultural Practices

S. No	Variables	Classification	Districts				Total No. of Farmers with Percentage
			Namakkal	Salem	Dharmapuri	Tiruppur	
1	Plant Cultivation Type	Single	12 (42.86%)	23 (60.53%)	9 (24.32%)	23 (62.16%)	67 (47.86%)
		Multiple	16 (57.14%)	15 (39.47%)	28 (75.68%)	14 (37.84%)	73 (52.14%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					
2	Disease Identification Methods	Own	16 (57.14%)	19 (50.00%)	17 (45.95%)	20 (54.05%)	72 (51.43%)
		Help	12 (42.86%)	19 (50.00%)	20 (54.05%)	17 (45.95%)	68 (48.57%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					
3	Preventive Practices	Yes	22 (78.57%)	22 (57.89%)	19 (51.35%)	20 (54.05%)	83 (59.29%)
		No	6 (21.43%)	16 (42.11%)	18 (48.65%)	17 (45.95%)	57 (40.71%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					
4	Management Practices	Yes	13 (46.43%)	14 (36.84%)	21 (56.76%)	21 (56.76%)	69 (49.29%)
		No	15 (53.57%)	24 (63.16%)	16 (43.24%)	16 (43.24%)	71 (50.71%)
		Total No.	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)
		Farmers with Percentage					

Analysis of preventive practices showed that 83 farmers (59.29% of 140) followed preventive practices, while the remaining 57 farmers (40.71% of 140) did not. Based on the district-wise analysis, 22 farmers (78.57% of 28) in Namakkal district and 22 farmers (57.89% of 38) in Salem district followed preventive practices, followed by 20 farmers (54.05% of 37) in Tiruppur district. Analysis of management practices showed that 69 farmers (49.29% of 140) followed management practices, while the remaining 71 farmers (50.71% of 140) did not. Based on the district-wise analysis, 24 farmers (63.16% of 38) in Salem district did not follow management practices, while 21 farmers (56.76% of 37) in Tiruppur district did.

3.4 Two Dimensional Percentage Analyses of Type of Plant Cultivation and Management Techniques

To achieve the second objective of the fourth division and the third objective, cultivation types and plant management techniques were analyzed using a two-dimensional percentage analysis. In this division, both single- and multiple-plant cultivation, as well as single- and multiple-plant management techniques used by farmers, were examined. The results are presented in Table 5 and Table 6, respectively. Table 5 shows that 12 farmers (42.86% of 28) in Namakkal, 23 farmers (60.53% of 38) in Salem, 9 farmers (24.32% of 37) in Dharmapuri, and 23 farmers (62.16% of 37) in Tiruppur cultivate single crops. Among all crops, lemon is cultivated by the highest number of farmers, 14 (10.00% of 140), followed by chili, cultivated by 13 farmers

(9.29% of 140). Based on district-wise classification, the highest number of lemon cultivators is found in Salem district, where 6 farmers (15.79% of 38) grow lemon. This is followed by Tiruppur district, where 5 farmers (13.51% of 37) grow chili. In addition, Table 5 shows that 16 farmers (57.14% of 28) in Namakkal, 15 farmers (39.47% of 38) in Salem, 28 farmers (75.68% of 37) in Dharmapuri, and 14 farmers (37.84% of 37) in Tiruppur cultivate multiple plants. In district-wise classification, the highest number of farmers in Namakkal district (11, 7.86% of 140) cultivated brinjal, followed by 10 farmers (7.14% of 140) who cultivated chili. In Salem district, the highest number, 10 farmers (7.14% of 140), cultivated Lady's finger, ridge gourd, and bitter gourd, followed by 9 farmers (6.43% of 140) who cultivated chili. In Dharmapuri district, the highest number of farmers, 17 (12.14% of 140), cultivated tomato, followed by 16 farmers (11.43% of 140) who cultivated ridge gourd. Similarly, in Tiruppur district, the highest number of farmers (11, or 7.86% of 140) cultivated lemon, followed by 10 farmers (7.14% of 140) who cultivated bitter gourd. Among all the plants, tomato is cultivated by the highest number of farmers in Dharmapuri, with 17 farmers (12.14% of 140), followed by ridge gourd, cultivated by 16 farmers (11.43% of 140) in the same district. Overall, the highest number of farmers, 42 (30.00% of 140), cultivate bitter gourd, followed by 41 farmers (29.29% of 140) who cultivate ridge gourd.

Table 5. District-wise Classification of Types of Plant Cultivation

S. No	Variables	Classification	Districts				Total No. of Farmers with Percentage
			Namakkal	Salem	Dharmapuri	Tiruppur	
1	Plant Cultivation (Single Plant)	Tomato	1 (3.57%)	3 (7.89%)	0 (0.00%)	4 (10.81%)	8 (5.71%)
		Brinjal	0 (0.00%)	3 (7.89%)	1 (2.70%)	3 (8.11%)	7 (5.00%)
		Lady's Finger	1 (3.57%)	1 (2.63%)	1 (2.70%)	1 (2.70%)	4 (2.86%)
		Chilli	3 (10.71%)	3 (7.89%)	2 (5.41%)	5 (13.51%)	13 (9.29%)
		Ridge Gourd	1 (3.57%)	4 (10.53%)	1 (2.70%)	4 (10.81%)	10 (7.14%)
		Bitter Gourd	2 (7.14%)	3 (7.89%)	3 (8.11%)	3 (8.11%)	11 (7.86%)
		Lemon	4 (14.29%)	6 (15.79%)	1 (2.70%)	3 (8.11%)	14 (10.00%)
		Total No. Farmers with Percentage	12 (42.86%)	23 (60.53%)	9 (24.32%)	23 (62.16%)	67 (47.86%)
2	Plant Cultivation (Multiple Plants)	Tomato	8 (5.71%)	8 (5.71%)	17 (12.14%)	7 (5.00%)	40 (28.57%)
		Brinjal	11 (7.86%)	7 (5.00%)	15 (10.71%)	6 (4.29%)	39 (27.86%)
		Lady's Finger	7 (5.00%)	10 (7.14%)	12 (8.57%)	6 (4.29%)	35 (25.00%)
		Chilli	10 (7.14%)	9 (6.43%)	15 (10.71%)	5 (3.57%)	39 (27.86%)
		Ridge Gourd	9 (6.43%)	10 (7.14%)	16 (11.43%)	6 (4.29%)	41 (29.29%)
		Bitter Gourd	7 (5.00%)	10 (7.14%)	15 (10.71%)	10 (7.14%)	42 (30.00%)
		Lemon	8 (5.71%)	7 (5.00%)	9 (6.43%)	11 (7.86%)	35 (25.00%)
		Total No. Farmers with Percentage	16 (57.14%)	15 (39.47%)	28 (75.68%)	14 (37.84%)	73 (52.14%)

From Table 6, it was identified that 12 farmers (42.86% of 28) in Namakkal district, 23 farmers (60.53% of 38) in Salem, 9 farmers (24.32% of 37) in Dharmapuri, and 23 farmers (62.16% of 37) in Tiruppur followed a single plant management technique on their farm. The highest number, 6 farmers (15.79% of 38) in Salem district, adopted insect control methods, followed by 5 farmers (13.51% of 37) in Tiruppur district who followed watering practices and Organic solutions. Overall, the maximum number of farmers, 13 (9.29% of 140), adopted fungicide/bactericide and insect control techniques, followed by 10 farmers (7.14% of 140) who used organic solutions. In addition, Table 6 presents details of the multiple plant management techniques used by farmers. The highest number of farmers, 24 (17.14% of 140), adopted the disease-resistant varieties technique in the Salem and Dharmapuri districts, followed by 23 farmers (16.43% of 140) who used

insect control in the Tiruppur district. In the district-wise classification, the majority of farmers in Namakkal district (20, 14.29% of 140) adopted fungicide/bactericide use, followed by 18 farmers (12.86% of 140) who practiced good sanitation and used disease-resistant varieties. In Salem district, 24 farmers (17.14% of 140) adopted disease-resistant varieties, followed by 21 farmers (15.00% of 140) who used organic solutions. Similarly, in Dharmapuri district, 24 farmers (17.14% of 140) adopted disease-resistant varieties, followed by 22 farmers (15.71% of 140) who used organic solutions and fungicides/bactericides. In Tiruppur district, 23 farmers (16.43% of 140) used insect control methods, followed by 22 farmers (15.71% of 140) who practiced good sanitation and used disease-resistant varieties and fungicide/bactericide. Overall, 88 farmers (62.86% of 140) adopted the disease-resistant variety technique, followed by 84 farmers (60.00% of 140) who used fungicide/bactericide.

Table 6. District-wise Classification of Farmers' Plant Management Techniques

S. No	Variables	Classification	Districts				Total No. of Farmers with Percentage
			Namakkal	Salem	Dharmapuri	Tiruppur	
1	Management Techniques (Single Plant)	Good	3 (10.71%)	3 (7.89%)	1 (2.70%)	2 (5.41%)	9 (6.43%)
		Sanitation					
		Disease-Resistant Varieties	0 (0.00%)	4 (10.53%)	1 (2.70%)	1 (2.70%)	6 (4.29%)
		Watering Practices	2 (7.14%)	1 (2.63%)	1 (2.70%)	5 (13.51%)	9 (6.43%)
		Air Circulation	0 (0.00%)	3 (7.89%)	2 (5.41%)	2 (5.41%)	7 (5.00%)
		Fungicides/Bactericides	4 (14.29%)	4 (10.53%)	1 (2.70%)	4 (10.81%)	13 (9.29%)
		Organic Solutions	2 (7.14%)	2 (5.26%)	1 (2.70%)	5 (13.51%)	10 (7.14%)
		Insect Control	1 (3.57%)	6 (15.79%)	2 (5.41%)	4 (10.81%)	13 (9.29%)
		Total No. Farmers with Percentage	12 (42.86%)	23 (60.53%)	9 (24.32%)	23 (62.16%)	67 (47.86%)
2	Management Techniques (Multiple)	Good	18 (12.86%)	16 (11.43%)	15 (10.71%)	22 (15.71%)	71 (50.71%)
		Sanitation					
		Disease-Resistant Varieties	18 (12.86%)	24 (17.14%)	24 (17.14%)	22 (15.71%)	88 (62.86%)
		Watering Practices	14 (10.00%)	20 (14.29%)	19 (13.57%)	17 (12.14%)	70 (50.00%)
		Air Circulation	15 (10.71%)	15 (10.71%)	19 (13.57%)	16 (11.43%)	65 (46.43%)
		Fungicides/Bactericides	20 (14.29%)	20 (14.29%)	22 (15.71%)	22 (15.71%)	84 (60.00%)
		Organic Solutions	14 (10.00%)	21 (15.00%)	22 (15.71%)	21 (15.00%)	78 (55.71%)
		Insect Control	10 (7.14%)	18 (12.86%)	17 (12.14%)	23 (16.43%)	68 (48.57%)
		Total No. Farmers with Percentage	28 (20.00%)	38 (27.14%)	37 (26.43%)	37 (26.43%)	140 (100%)

3.5 Linear Regression Analysis of Socio-Profiles in Relation to Farmers Families, Practices and Property

To identify significant relations between farmers' socio-profiles and their family participation in farming, property ownership, and agricultural practices, a regression analysis was performed. Table 7 presents the results highlighting the significant associations between socio-profile variables and farmers' family participation, practices, and property. From Table 7, the p-value for family type is 0.0371, which is less than 0.05, indicating a statistically significant relationship. The age factor was also significantly associated with family type. Similarly, the experience factor is related to the farmers' families, practices, and property. The p-value for the management practices factor is 0.0308, which is also less than 0.05, indicating a statistically significant relationship. This suggests that the experience factor is significantly associated with farmers' management practices. Farmers' practice methods were also related to their families, agricultural practices, and property. The p-values for disease identification methods (0.0061) and management practices (0.0038) are both less than 0.05, indicating statistically significant relationships. This suggests that farmers' practice methods are significantly associated with both disease identification methods and management practices.

Table 7. Regression Analysis of Farmers' Families and Practices in Relation to their Socio-Profile

Variables	Classification	F	R ²	p
Age	Family Type	4.4289	0.0310	0.0371
	No. of Family Members	0.02787	0.0002	0.8676
	Family Participation	1.8006	0.0128	0.1818
	Property Type	3.7829	0.0266	0.0538
	Area of Land	0.0495	0.0003	0.8241
	Plant Cultivation Type	0.1145	0.0008	0.7355
	Disease Identification Methods	0.0847	0.0006	0.7713
	Preventive Practices	0.1209	0.0008	0.7285
	Management Practices	0.4455	0.0032	0.5055
Experience	Family Type	0.5170	0.0037	0.4733
	No. of Family Members	0.1685	0.0012	0.6820
	Family Participation	0.4494	0.0032	0.5037
	Property Type	0.0059	0.0000	0.9387
	Area of Land	0.1627	0.0011	0.6872
	Plant Cultivation Type	1.0965	0.0078	0.2968
	Disease Identification Methods	2.7514	0.0195	0.0994
	Preventive Practices	0.3986	0.0028	0.5288
	Management Practices	4.7591	0.0333	0.0308
Practice Method	Family Type	0.0003	0.0000	0.9846
	No. of Family Members	0.0050	0.0000	0.9432
	Family Participation	0.1006	0.0007	0.7515
	Property Type	1.0247	0.0073	0.3131
	Area of Land	1.8711	0.0133	0.1735
	Plant Cultivation Type	0.2853	0.0020	0.5941
	Disease Identification Methods	7.7558	0.0532	0.0061
	Preventive Practices	0.9719	0.0069	0.3259
	Management Practices	8.6194	0.0587	0.0038

3.6 Critical Analysis of the Study

The study focused on Plant disease classification, leaf disease detection, and prevention using hybrid techniques such as CNN combined with RNN, LSTM, VGG16, Decision Tree, kNN, and others. Based on the analysis of previous studies (refer to Table 1), it was observed that the combination of CNN with HBOA has been used only for plant disease detection, not classification. CNN combined with LDI-NET achieved the highest classification accuracy but was inefficient for disease detection. In contrast, CNN combined with

LSTM achieved over 98% accuracy for both disease detection and classification, outperforming the CNN and RNN combination. From this analysis, it was concluded that CNN combined with LSTM is the most efficient hybrid method and is recommended as a direction for future research. A comprehensive critical analysis was applied to the divisions: socio-profile of the farmers, farmers' family and their property classification, and farmers' agricultural practices. The age group 30-40 years had the highest number of farmers involved in agricultural practices, with 37 farmers (26.43% of 140), followed by the age group above 60 years with 36 farmers (25.71%). In terms of farming experience, the largest group comprised 41 farmers (29.29%) with 30 years of experience, followed by 38 farmers (27.14%) with 10 years of experience. Regarding farming practice, 74 farmers (52.86%) were involved part-time, while 66 farmers (47.14%) were engaged full-time. Based on family type, 72 farmers (51.43%) lived in nuclear families, and 68 farmers (48.57%) lived in joint families. By number of family members, the highest number, 38 farmers (27.14%), had families with 9 to 12 members, followed by 35 farmers (25.00%) with families of 3 to 5 members. In terms of family involvement in farming, 72 farmers (51.43%) had family members partially involved, while 68 farmers (48.57%) reported full involvement. This analysis found that farmers in the 30-40 years age group (26.43%) typically have around 10 years of experience, are involved in farming part-time, and live in nuclear families with 3-5 members. These families tend to be fully involved in farming. However, these farmers often lack adequate knowledge for disease identification and preventive measures compared to more experienced farmers, and they are only beginning to adopt proper management practices. In contrast, farmers over 60 years old (25.71%) generally have about 30 years of farming experience, are engaged full-time, and live in joint families with 9 to 12 members. Their family members are only partially involved in farming. These experienced farmers rely on their own knowledge for disease identification and tend to follow preventive practices, but do not strictly adhere to formal management practices.

3.7 Discussion

The findings reveal important insights into farmers' socio-economic conditions, agricultural practices, and plant disease management approaches in the western districts of Tamil Nadu. The survey results indicate that most farmers belong to the 30-40 years age group (26.43%), followed closely by farmers above 60 years (25.71%). Farmers in the younger age group were mostly engaged in part-time farming and lived in smaller nuclear families. In contrast, older farmers with more than 30 years of experience were primarily involved in full-time farming and depended on traditional farming knowledge for disease identification and management. Similar observations were reported in earlier farmer-based agricultural surveys, where experienced farmers relied more on practical knowledge and conventional disease management practices, while younger farmers showed greater interest in adopting modern agricultural technologies and smart farming techniques. The study also revealed that multiple crop cultivation was more common than single crop cultivation, particularly in Dharmapuri district, where tomato and ridge gourd cultivation were predominant. Disease-resistant varieties and fungicide/bactericide applications were the most widely adopted management techniques among farmers. These findings are consistent with previous agricultural studies that emphasized the importance of integrated disease management practices for improving crop productivity and reducing losses caused by plant diseases. The literature review demonstrated that hybrid deep learning techniques significantly improve plant disease detection and classification accuracy. Among the reviewed methods, CNN combined with LSTM achieved consistently high performance for both disease detection and classification, with accuracy levels above 98%. CNN-LSTM models effectively combine spatial feature extraction and temporal learning, enabling accurate recognition of complex disease patterns in plant leaves. Previous studies by Hepzibah Elizabeth David et al., Vasumathi and Kamarasan, and Rama Chandran et al. also confirmed the superiority of CNN-LSTM models for agricultural disease diagnosis. In comparison, CNN-RNN and CNN-LDI-NET models achieved comparatively lower or task-specific performance. Integrating survey findings with the literature highlights a significant research implication. Although advanced AI-based disease detection systems demonstrate very high accuracy in research environments, many farmers, particularly younger and part-time farmers, still depend on manual observation and traditional disease identification methods. This indicates a gap between technological advancements and adoption at the field level. Therefore, there is a strong need to develop affordable, user-friendly, and mobile-

based AI systems that can assist farmers in real-time disease identification and management. Such systems can improve early detection, reduce crop losses, and support sustainable agricultural practices in rural farming communities. Regression analysis further confirmed statistically significant relationships between socio-profile factors and agricultural practices. Family type was significantly associated with age, while farming experience significantly influenced management practices. Practice methods were strongly associated with disease identification and management techniques. The following Table 8 illustrates the Correlation matrix relationships between Socio profile and practice methods. The correlation matrix also indicated positive relationships between practice methods and disease management variables, suggesting that farmers who are actively engaged in farming tend to adopt better disease management approaches. Despite these valuable findings, the study has certain limitations. The survey was conducted in only four districts of western Tamil Nadu, with a relatively small sample size of 140 farmers after data cleaning. The use of convenience sampling may also limit the generalizability of the findings to all farming communities. In addition, the research relied mainly on questionnaire-based responses and literature analysis rather than real-time implementation of deep learning models in field conditions. Future research can focus on collecting larger datasets from multiple regions, integrating real-time IoT-based monitoring systems, and implementing CNN-LSTM models directly in smartphone applications for practical agricultural use. Such developments can bridge the gap between advanced AI research and real-world farming applications.

Table 8. Correlation matrix relationships between Socio profile and practice methods

	District	Age	Experience	FT/PT	Family type	Family Member	Participation	Property	Land	Plant type	Diseases Identification	Preven table	Managable
District	1.0000												
Age	-0.0076	1.0000											
Experience	-0.1090	0.0250	1.0000										
FT/PT	-0.0115	-0.0874	-0.1075	1.0000									
Family type	0.0223	-0.1763	-0.0611	0.0016	1.0000								
Family	-0.1788	0.0142	-0.0349	0.0061	0.1352	1.0000							
Member													
Participation	0.1363	0.1135	-0.0570	0.0270	-0.0564	-0.0452	1.0000						
Property	-0.1519	0.1633	-0.0066	-0.0859	-0.1429	0.0578	-0.0572	1.0000					
Land	0.1639	-0.0189	-0.0343	-0.1157	-0.0080	-0.0909	-0.0797	-0.1666	1.0000				
Plant type	-0.0433	0.0320	-0.0888	-0.0454	-0.0131	-0.0003	-0.0441	-0.1573	0.0427	1.0000			
Diseases	0.0223	0.0248	-0.1398	0.2307	-0.0580	0.0195	0.0866	0.0000	-0.0080	0.0727	1.0000		
Identification													
Preventable	0.1641	0.0296	-0.0537	0.0836	-0.0199	0.0405	0.0781	-0.0436	-0.0040	-0.0792	0.0091	1.0000	
Managable	-0.1201	0.0567	-0.1826	0.2425	0.0719	0.1541	-0.0147	-0.0143	-0.0442	-0.0292	0.0719	0.0027	1.0000

4. Conclusion

This study examined the use of hybrid deep learning methods, specifically CNN combined with LSTM, to improve plant leaf disease detection. CNN-LSTM was the most effective model, achieving over 98% accuracy in identifying diseases. A survey of 140 farmers in four districts of Western Tamil Nadu revealed differences in farming methods by age; younger farmers often use modern techniques, while older farmers stick to traditional methods. The study found a significant link between farmers' age, family structure, and their disease management practices. The research highlights the need for training and access to technology for farmers.

5. Acknowledgments

Author Contributions: Mrs.P.Valarmathi and Dr. I. Laurence Aroquiaraj are the authors of this research article. The authors' contributions are listed below. Mrs. P. Valarmathi collected references for the literature survey and compiled it. Through that survey, she identified the research gap and defined the objective of the paper. Dr. I. Laurence Aroquiaraj suggested the research methodology. Mrs. P. Valarmathi generated a questionnaire to collect data from the farmers. Dr. I. Laurence Aroquiaraj corrected the questionnaire and suggested selecting the research model. Based on his advice, Mrs. P. Valarmathi completed the data collection, analysis, and consolidation of results. Dr. I. Laurence Aroquiaraj verified the results and advised incorporating them into the paper. Based on his direction, Mrs. P. Valarmathi wrote the content and converted it into a research article. Finally, Dr. I. Laurence Aroquiaraj made corrections to the article and advised publishing it in high-impact journals such as SCOPUS/SCI/SCIE/SSCI, etc.

Funding: This research received no external funding

Conflicts of Interest: The authors declare no conflict of interest.

References

- [1] Liao, F.; Feng, X.; Li, Z.; Wang, D.; Xu, C.; Chu, G.; Ma, H.; Yao, Q.; Chen, S. A Hybrid CNN-LSTM Model for Diagnosing Rice Nutrient Levels at the Rice Panicle Initiation Stage. *J. Integr. Agric.* **2024**, *23*(2), 711–723. <https://doi.org/10.1016/j.jia.2023.05.032>
- [2] David, H. E.; Ramalakshmi, K.; Venkatesan, R.; Hemalatha, G. Tomato Leaf Disease Detection Using Hybrid CNN-RNN Model. In *Smart Intelligent Computing and Communication Technology*; **2021**; pp 593–597. <https://doi.org/10.3233/APC210108>
- [3] Pant, K.; Pant, B.; Bordoloi, D. Automatic Classification of Plant Leaf Disease Using a Novel Hybrid Approach of LSTM-CNN. *Ilkogretim Online - Elementary Education Online* **2021**, *20*(3), 4220–4228. <https://doi.org/10.17051/ilkonline.2021.03.436>
- [4] Kanakala, S.; Ningappa, S. Detection and Classification of Diseases in Multi-Crop Leaves Using LSTM and CNN Models. *J. Innov. Image Process.* **2025**, *7*(1), 161–181. <https://doi.org/10.36548/jiip.2025.1.008>
- [5] Pan, Y. Leaf Disease Detection and Classification with a CNN-LSTM Hybrid Model. In *Proceedings of the 2nd International Conference on Machine Learning and Automation*; **2024**; pp 7–20. <https://doi.org/10.54254/2755-2721/104/20240902>
- [6] Jain, S.; Ramesh, D. AI Based Hybrid CNN-LSTM Model for Crop Disease Prediction: An ML Advent for Rice Crop. In *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*; **2021**; pp 1–6. <https://doi.org/10.1109/ICCCNT51525.2021.9579587>
- [7] Le, S. M.; Ardekani, I.; Abdulla, W. H. Optimizing Plant Disease Classification with Hybrid Convolutional Neural Network–Recurrent Neural Network and Liquid Time-Constant Network. *Appl. Sci.* **2024**, *14*, 9118. <https://doi.org/10.3390/app14199118>

- [8] Sameera, P.; Deshpande, A. A. Disease Detection and Classification in Pomegranate Fruit Using Hybrid Convolutional Neural Network with Honey Badger Optimization Algorithm. *Int. J. Food Prop.* **2024**, 27(1), 815–837. <https://doi.org/10.1080/10942912.2024.2365927>
- [9] Chandran, V. R.; Jyothika, M.; Nandhini, M.; Neelima, P.; Neeraja, P. Tomato Leaves Disease Detection Using Hybrid Model CNN-LSTM. *Int. J. Res. Appl. Sci. Eng. Technol.* **2024**, 12(3), 2248–2256. <https://doi.org/10.22214/ijraset.2024.59173>
- [10] Hukkeri, G.; Soundarya, B.; Gururaj, H.; Ravi, V. Classification of Various Plant Leaf Disease Using Pretrained Convolutional Neural Network on ImageNet. *Open Agric. J.* **2024**, 18, e18743315305194. <https://doi.org/10.2174/0118743315305194240408034912>
- [11] Khaki, S.; Wang, L.; Archontoulis, S. V. A CNN-RNN Framework for Crop Yield Prediction. *Front. Plant Sci.* **2020**, 10, 1750. <https://doi.org/10.3389/fpls.2019.01750>
- [12] Kumar, R.; Jindal, V. A Survey of Plant Disease Detection Techniques Based on Image Processing and Machine Learning. *Int. J. Health Sci.* **2022**, 6(S6), 1954–1967. <https://doi.org/10.53730/ijhs.v6nS4.10096>
- [13] Anwar, B.; Morsey, M. M.; Hegazy, I.; Fayed, Z. T.; El-Arif, T. Hybrid CNN-RNN Architecture for Accurate Tomato Disease with Xception-GRU. *Int. J. Intell. Comput. Inf. Sci.* **2024**, 24(4), 60–72. <https://doi.org/10.21608/ijicis.2024.333285.1363>
- [14] Chaudhary, A.; Gupta, M.; Tiwari, U. Crop Disease Detection Using Deep Learning Models. *Int. J. Innov. Sci. Res. Technol.* **2023**, 8(12), 1189–1197
- [15] Vasumathi, M. T.; Kamarasan, M. An Effective Pomegranate Fruit Classification Based on CNN-LSTM Deep Learning Models. *Indian J. Sci. Technol.* **2021**, 14(16), 1310–1319. <https://doi.org/10.17485/IJST/v14i16.432>
- [16] Gobinath, V.; Ilakiya, V.; Monikasri, B.; Nandhini, R.; Shalene, V. Plant Disease Prediction Using Hybrid Model. *Int. J. Eng. Res. Technol.* **2023**, 11(3), 1–9.
- [17] Xing, D.; Wang, Y.; Sun, P.; Huang, H.; Lin, E. A CNN-LSTM-Att Hybrid Model for Classification and Evaluation of Growth Status under Drought and Heat Stress in Chinese Fir (*Cunninghamia lanceolata*). *Plant Methods* **2023**, 19, 66, 1–13. <https://doi.org/10.1186/s13007-023-01044-8>
- [18] Tasdelen, A.; Sen, B. A Hybrid CNN-LSTM Model for Pre-miRNA Classification. *Sci. Rep.* **2021**, 11, 14125, 1–9. <https://doi.org/10.1038/s41598-021-93656-0>
- [19] Yang, B.; Li, M.; Li, F.; Wang, Y.; Liang, Q.; Zhao, R.; Li, C.; Wang, J. A Novel Plant Type, Leaf Disease and Severity Identification Framework Using CNN and Transformer with Multi-Label Method. *Sci. Rep.* **2024**, 14, 11664, 1–15. <https://doi.org/10.1038/s41598-024-62452-x>
- [20] Khan, B.; Das, S.; Fahim, N. S.; Banerjee, S.; Khan, S.; Al-Sadoon, M. K.; Al-Otaibi, H. S.; Islam, A. R. M. T. Bayesian Optimized Multimodal Deep Hybrid Learning Approach for Tomato Leaf Disease Classification. *Sci. Rep.* **2024**, 14, 21525, 1–30. <https://doi.org/10.1038/s41598-024-72237-x>
- [21] Salini, R.; Latha, G. C. P.; Khilar, R. Deep Hybrid Classification Model for Leaf Disease Classification of Underground Crops. *Web Intell.* **2024**, 22, 443–465. <https://doi.org/10.3233/WEB-230180>
- [22] Shwetha, V.; Patil, R. R.; Muthusamy, A.; Harish, S. V.; Laxmi, V.; Girish, P. Comprehensive Leaf Spot Disease Detection Using a Curated Image Dataset of Jasmine Plant Leaves. *SSRN* **2025**. <https://ssrn.com/abstract=5252632>