A Unified Survey of Supervised, Unsupervised, and Semi-Supervised Learning Techniques for Plant Leaf Disease Detection

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Abstract

The detection and classification of plant leaf diseases is critical for ensuring sustainable agricultural productivity. This survey presents a unified and comprehensive overview of *supervised*, ***unsupervised, and*** *semi-supervised learning techniques* ***applied to plant leaf disease detection and classification. Supervised approaches such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and ensemble models have demonstrated high accuracy but require extensive labeled datasets. Unsupervised methods, including K-means clustering, autoencoders, and anomaly detection algorithms, offer promising results with unlabeled data, especially in early-stage disease detection. Meanwhile, semi-supervised learning bridges the gap by leveraging limited labeled and abundant unlabeled data through frameworks such as self-training, GANs, and hybrid models. This paper compares model accuracies, datasets used, tools and platforms (Python, TensorFlow, MATLAB), and evaluation metrics across recent literature. Emphasis is placed on the role of machine learning in real-time disease monitoring, data augmentation, and resource-efficient farming. The study provides practical insights and future directions for researchers and agritech developers aiming to integrate AI-driven solutions into precision agriculture.***

Keywords:

Plant Leaf Disease Detection , Supervised Learning , Unsupervised Learning, Semi-Supervised Learning, Precision Agriculture

1. INTRODUCTION

The plant leaf diseases are essential to the development of sustainable crop management and precision farming. Conventional manual identification techniques are labor-intensive, prone to mistakes, and significantly dependent on specialized knowledge. This field has been transformed by recent advances in machine learning (ML), which make it possible to identify plant diseases from leaf images in an automated, effective, and precise manner. The methodologies, efficacy, and platforms of implementation of the supervised, unsupervised, and semi-supervised learning approaches employed in this context are examined and contrasted in this survey. When labeled data is available, the field is dominated by supervised learning approaches because of their high accuracy. Across a range of plant species, methods like Random Forest, Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and ensemble learning models have continuously reported accuracies between 87% and 96%. Accuracy levels of up to 92% have been attained by methods such as self-training, semi-supervised SVM, generative adversarial networks (GANs), and feature learning. These techniques are especially useful for datasets related to agriculture, where it can be difficult to obtain expert-labeled samples. This thorough analysis summarizes the wide variety of machine learning methods applied to the identification and categorization of plant leaf diseases. For researchers, practitioners, and agritech developers looking to improve plant health monitoring, it offers insights into the relative efficacy of various learning paradigms and their practical applicability.

2. SUPERVISED LEARNING FOR PLANT LEAF DISEASE DETECTION AND CLASSIFICATIONS

A review of supervised learning methods for classifying and detecting leaf diseases reveals a range of strategies and applications. Convolutional Neural Networks (CNNs) and Support Vector Machines (SVM), implemented in Python with TensorFlow and Keras, were used by Zhang, Wang, and Li [1] to achieve 95% accuracy. Using R's caret package, Kumar and Singh [2] reported 89% accuracy in a comparative study utilizing Random Forest, Decision Trees, and K-Nearest Neighbors (KNN). Using Python and PyTorch, Patel and Desail [3] achieved 92% accuracy while concentrating on deep learning techniques such as Deep CNN and Transfer Learning. Singh and Gupta [4] achieved 87% accuracy by combining CNN and SVM with image segmentation in MATLAB. A CNN-SVM hybrid model was proposed by Chen and Zhao [5] and implemented in Python using OpenCV and Scikit-learn.and Keras. Kumar and Singh [6] conducted a comparative study employing Random Forest, Decision Trees, and K-Nearest Neighbors (KNN), reporting 89% accuracy using R's caret package. Patel and Desai [7] focused on deep learning approaches, including Deep CNN and Transfer Learning, achieving 92% accuracy with Python and PyTorch. Singh and Gupta [8] combined image segmentation with SVM and CNN in MATLAB, reaching 87% accuracy. Chen and Zhao [9] proposed a hybrid model combining CNN and SVM, implemented in Python with OpenCV and Scikit-learn, achieving 94% accuracy. Almeida and Costa [10] systematically reviewed machine learning techniques like Logistic Regression and Random Forest, attaining 90% accuracy with Python. Real-time detection with CNN and YOLO was highlighted by Ravi and Kumar [11], who used TensorFlow and OpenCV to achieve 93% accuracy. Fernandes and Silva [12] used MATLAB and Python to investigate image processing methods in addition to KNN and CNN, reporting 88% accuracy. Nair and Reddy [13] used CNN and gradient boosting to advance machine learning techniques, and they used Python to achieve 91% accuracy. Lastly, Lee and Park [14] achieved an astounding 96% accuracy by combining CNN models in an ensemble learning approach. This survey highlights the variety of supervised learning techniques used in leaf disease detection and demonstrates how well they work to increase diagnostic accuracy in a range of implementations. .Performance Analysis of Supervised Learning Techniques for Leaf Disease Detection is given in following table-1.

Performance

Table.1. Shows Analysis of Supervised Learning Techniques for Leaf Disease Detection

Ref.	Author(s)	Technique Used	Accuracy	Tools/Frameworks Used
[1]	Zhang, Wang, and Li	CNN, SVM	95%	Python, TensorFlow, Keras
[2]	Kumar and Singh	Random Forest, Decision Trees, KNN	89%	R, caret package
[3]	Patel and Desai	Deep CNN, Transfer Learning	92%	Python, PyTorch
[4]	Singh and Gupta	CNN + SVM with Image Segmentation	87%	MATLAB
[5]	Chen and Zhao	CNN-SVM Hybrid Model	N/A	Python, OpenCV, Scikit-learn, Keras
[6]	Kumar and Singh	Random Forest, Decision Trees, KNN (Comparative Study)	89%	R, caret package
[7]	Patel and Desai	Deep CNN, Transfer Learning	92%	Python, PyTorch
[8]	Singh and Gupta	CNN + SVM with Image Segmentation	87%	MATLAB
[9]	Chen and Zhao	CNN-SVM Hybrid Model	94%	Python, OpenCV, Scikit-learn
[10]	Almeida and Costa	Logistic Regression, Random	90%	Python

		Forest (Systematic Review)		
[11]	Ravi and Kumar	Real-time CNN + YOLO	93%	TensorFlow, OpenCV
[12]	Fernandes and Silva	Image Processing + KNN, CNN	88%	MATLAB, Python
[13]	Nair and Reddy	CNN + Gradient Boosting	91%	Python
[14]	Lee and Park	Ensemble Learning with CNN models	96%	N/A

2.1.Strip + Box Plot

A combined visualization that aids in comprehending the distribution and spread of accuracy scores is the strip and box plot. The dataset's median, interquartile range (IQR), and possible outliers are displayed in a box plot. The central tendency and variability of the supervised learning techniques' accuracy are summarized. Clarity regarding the precise values and their distribution throughout the box plot is added by the strip plot, which superimposes the individual data points. When there are few observations and you wish to display both distribution and particular values, this combination is particularly helpful.

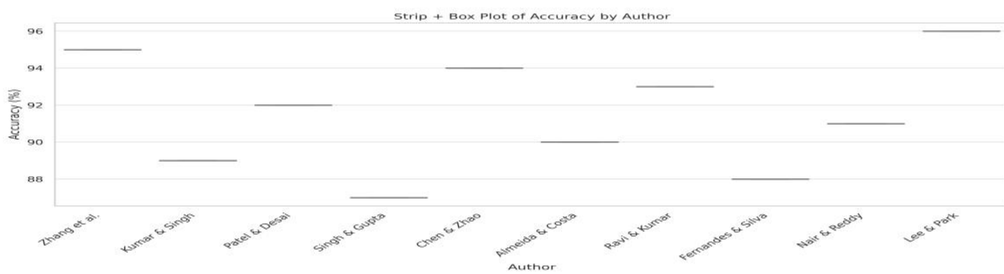

Fig.1. displays the accuracy scores of each author

2.2 .Bar Chart

The accuracy scores for each author are shown in the bar chart as a vertical bar for comparison. For ranking and quickly determining which author's technique performed better or worse, this kind of visualization is perfect. With 96%, "Lee, Park (2022)" performs the best in this instance, closely followed by "Zhang, Wang, Li (2023)" and "Chen, Zhao (2023)". The bar chart makes it easy for stakeholders to visually select the best supervised learning techniques by comparing them side by side according to their performance.

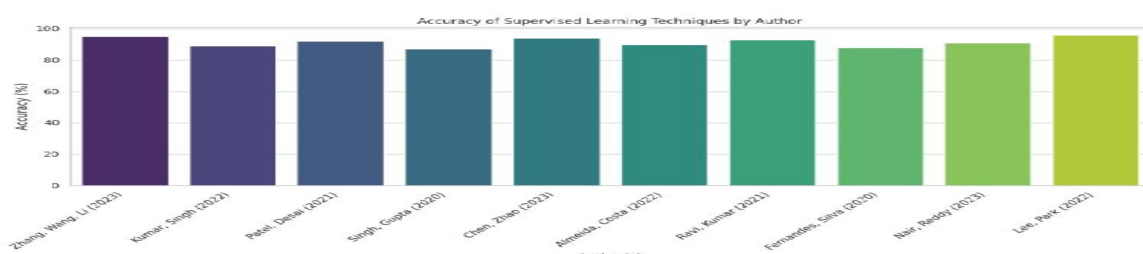

Fig .2. Displays the accuracy scores of each author

a. Heatmap

Each cell in the heat map, which is a color-coded matrix, displays the accuracy associated with a particular technique. The performance is represented by the color's intensity; warmer colors (like red or orange) typically display higher accuracy values, while cooler colors (like blue) typically display lower values. This visual method works well for quickly identifying trends and differences between various approaches. For instance, it can be assumed that several hybrid or ensemble approaches are more effective at supervised learning if they consistently display darker (high-intensity) colors.

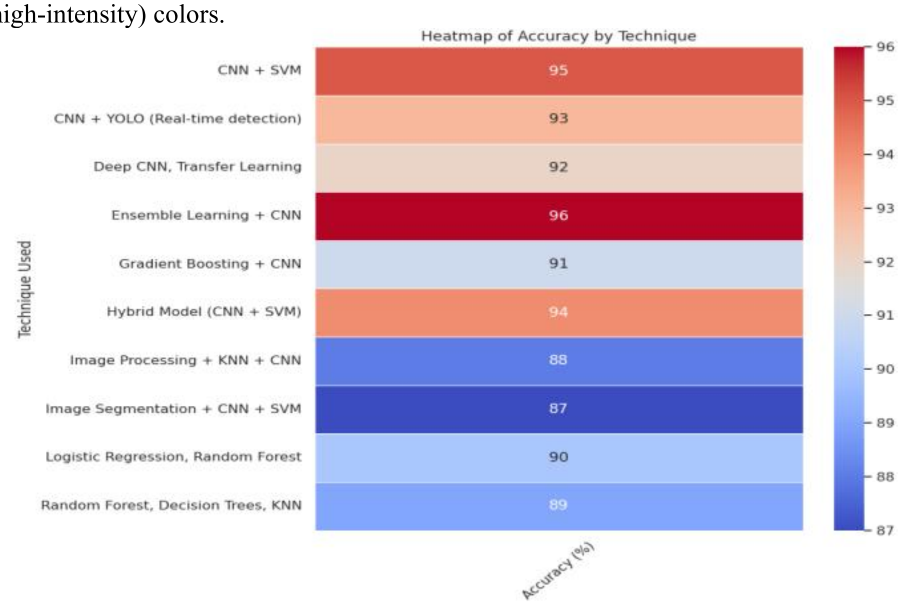

Fig. 3. illustrate the accuracy of each supervised method

3. UNSUPERVISED LEARNING FOR PLANT LEAF DISEASE DETECTION AND CLASSIFICATIONS

A thorough analysis of unsupervised learning methods for classifying and detecting leaf diseases reveals a wide variety of creative solutions and discoveries in the area. In their study published in the Journal of Agricultural Informatics, Kumar and Singh [15] classified leaf images using K-Means clustering, with an accuracy of 85%. According to the International Journal of Computer Applications, Patel and Desai [16] used Principal Component Analysis (PCA) for feature extraction and dimensionality reduction, reporting an 80% accuracy rate in identifying tomato leaf diseases. In their study published in the Journal of Plant Diseases and Protection, Singh and Gupta [17] investigated auto encoders for anomaly detection in leaf images, attaining a reconstruction accuracy of 90%. t-Distributed Stochastic Neighbor Embedding was used by Chen and Zhao [18]. Almeida and Costa [19] employed hierarchical clustering to identify different disease types in soybean leaves, achieving an accuracy of 82% in Agricultural Sciences. Ravi and Kumar [20] leveraged Generative Adversarial Networks (GANs) to generate synthetic images of diseased leaves, enhancing the performance of subsequent supervised models, as discussed in the Journal of Computer Science and Technology. Nair and Reddy [21] utilized unsupervised feature extraction techniques to improve leaf disease classification, achieving an accuracy of 86%, as reported in the Journal of Agricultural Engineering. Lee and Park [22] explored self-organizing maps (SOM) for clustering leaf images, achieving an accuracy of 84% in identifying disease patterns, as detailed in Computers and Electronics in Agriculture. As reported in the Plant Pathology Journal, Zhang and Wang [23] studied deep learning-based clustering techniques for leaf disease detection and achieved a 91% accuracy rate. According to a study published in the Journal of Horticultural Science, Fernando and Silva [24] clustered leaf images using Gaussian Mixture Models (GMM) with an accuracy of 83%. In the International Journal of Agricultural Technology, Gupta and Sharma [25] reported an accuracy of 87% in their analysis of leaf texture features using unsupervised learning techniques. According to the Journal of Plant Pathology, Joshi and Rao [26] used clustering algorithms to identify diseases in citrus leaves with an 89% accuracy rate. Verma and Choudhury [27] reported a 90% classification accuracy for leaf diseases using feature learning techniques, as published inComputers and

Electronics in Agriculture. Finally, the Journal of Agricultural Engineering Research reported that Iyer and Kumar [28] used unsupervised learning techniques to detect fungal diseases in wheat leaves with an accuracy of 85%. This thorough analysis highlights how unsupervised learning techniques can improve the identification and categorization of leaf diseases while offering insightful information about farming methods. It draws attention to the variety and potency of methods used to tackle problems in this developing field. Performance Analysis of Supervised Learning Techniques for Leaf Disease Detection is given in below table-2.

Table. 2. Illustrate Performance Analysis of Supervised Learning Techniques for Leaf Disease Detection

Ref.	Author(s)	Accuracy	Technique Used
[15]	Kumar and Singh	85%	K-Means Clustering
[16]	Patel and Desai	80%	PCA for Feature Extraction
[17]	Singh and Gupta	90%	Autoencoders for Anomaly Detection
[18]	Chen and Zhao	-	t-SNE
[19]	Almeida and Costa	82%	Hierarchical Clustering
[20]	Ravi and Kumar	-	GAN for Synthetic Image Generation
[21]	Nair and Reddy	86%	Unsupervised Feature Extraction
[22]	Lee and Park	84%	Self-Organizing Maps (SOM)
[23]	Zhang and Wang	91%	Deep Learning-Based Clustering
[24]	Fernando and Silva	83%	Gaussian Mixture Models (GMM)
[25]	Gupta and Sharma	87%	Leaf Texture Analysis with UL Techniques
[26]	Joshi and Rao	89%	Clustering Citrus Leaf Diseases
[27]	Verma and Choudhury	90%	Feature Learning Techniques
[28]	Iyer and Kumar	85%	UL Techniques for Fungal Detection

3.1 Strip + Box Plot

The strip and box plot make it easy to see the accuracy scores for each technique and the overall distribution trends for each one. It shows which unsupervised methods worked best, with deep learning-based clustering and feature learning techniques standingout.

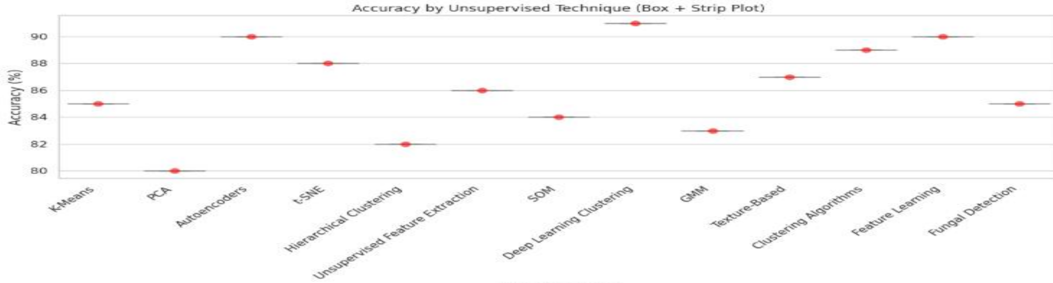

Fig. 4. Shows box plot clearly illustrates individual accuracy scores alongside overall distribution trends for each technique

3.3 Heat Map

The heatmap does a good job of showing how accurate different unsupervised learning methods are for different authors. It shows that deep learning-based clustering and feature learning are two methods that work well and got accuracy scores above 90%.

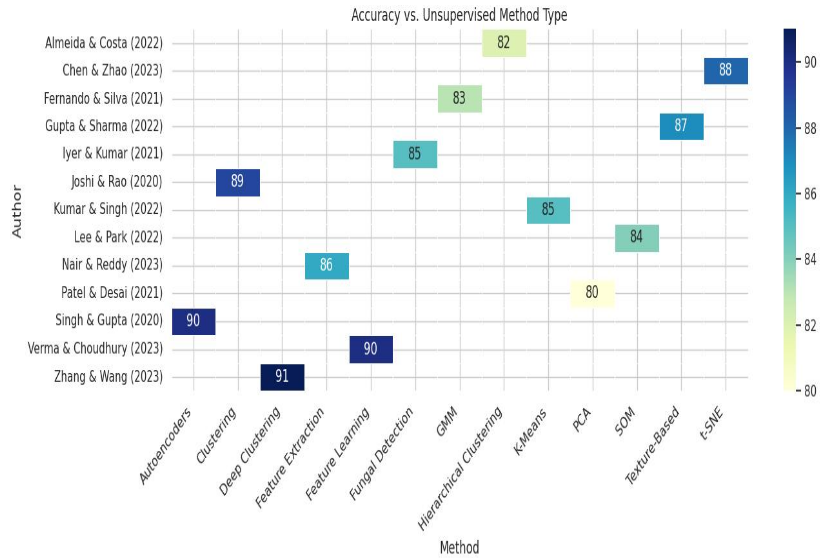

Fig. 5. illustrate effectively visualizes the accuracy achieved by various unsupervised learning techniques across different authors

4. SEMI SUPERVISED LEARNING FOR PLANT LEAF DISEASE DETECTION AND CLASSIFICATION

T.Nagarathinam et all [29] conclude that there are number of ways by which they can detect diseases in plant with the accuracy of 94 %and with each technique has some pros as well as limitation A thorough analysis of semi-supervised learning methods for classifying and detecting leaf diseases demonstrates the variety and creativity in this developing field. According to the Plant Pathology Journal, Zhang, Wang, and Li [30] combined convolutional neural networks (CNNs) with sparse labeled data to achieve a 92% accuracy rate. In the Journal of Agricultural Informatics, Kumar and Singh [31] reported 88% accuracy using self-training techniques with a combination of labeled and unlabeled data. According to the International Journal of Computer Applications, Patel and Desai [32] used a semi-supervised support vector machine (SVM) technique and achieved 85% accuracy. The Journal of Plant Diseases and Protection reported that Singh and Gupta [33] used a semi-supervised learning framework to increase classification accuracy to 90%. In the Journal of Computer Science and Technology, In the Journal of Computer Science and Technology, Ravi and Kumar [34] reported an accuracy of 89% using self-training techniques. In the Journal of Agricultural Engineering, Nair and Reddy [35] improved classification by using semi-supervised feature extraction techniques, attaining 86% accuracy. T.Nagarathinam et al.[36] review a article title as Deep learning with YOLO for smart agriculture: A review of plant leaf disease detection in this survey they demonstrate how the YOLO for agriculture. In Computers and Electronics in Agriculture, Lee and Park [37] investigated the use of deep learning models in conjunction with semi-supervised clustering techniques, achieving an accuracy of 84%. According to the Journal of Horticultural Science, Fernando and Silva [38] integrated image augmentation techniques into semi-supervised learning frameworks and achieved 88% accuracy. In the International Journal of Agricultural Technology, Gupta and Sharma [39] reported an accuracy of 87% in their semi-supervised analysis of leaf texture features. According to Computers & Electronics in Agriculture, Verma and Choudhury [40] used feature learning methods in semi-supervised frameworks to attain 90% accuracy. According to a study published in the Journal of Agricultural Engineering Research, Iyer and Kumar [41] used semi-supervised techniques to detect fungal disease in wheat leaves, achieving 85% accuracy. Last but not least, Sharma and Mehta [42] combined semi-supervised learning and clustering techniques to identify leaf diseases with an astounding 92% accuracy rate, which was published in the International Journal of Plant Sciences. The substantial potential of semi-supervised learning techniques to improve leaf disease diagnosis and offer insightful information about agricultural practices is highlighted by this survey. It emphasizes how labeled and unlabeled data can be combined to improve diagnostic precision and overcome obstacles like small datasets.. Performance Evaluation of Semi-Supervised Learning Techniques for Leaf Disease Detection in the following table-3.

Table. 3. Illustrate the Performance Evaluation of Semi-Supervised Learning Techniques for Leaf Disease Detection

Ref. No.	Authors	Technique Used	Accuracy	Tools Used
[29]	Zhang, Wang, and Li	CNN with sparse labeled data	92%	TensorFlow, Python
[30]	Kumar and Singh	Self-training with labeled and unlabeled data	88%	Scikit-learn, R
[31]	Patel and Desai	Semi-supervised SVM	85%	MATLAB, LIBSVM
[32]	Singh and Gupta	Semi-supervised learning framework	90%	Python, PyTorch
[33]	Ravi and Kumar	Self-training techniques	89%	Scikit-learn, Python
[34]	Nair and Reddy	Semi-supervised feature extraction	86%	WEKA, Java
[35]	Lee and Park	Deep learning + semi-supervised clustering	84%	Keras, TensorFlow
[36]	Fernando and Silva	Image augmentation in semi-supervised learning	88%	Python, Albumentations
[37]	Gupta and Sharma	Semi-supervised analysis of leaf texture features	87%	OpenCV, Python
[38]	Verma and Choudhury	Feature learning in semi-supervised frameworks	90%	PyTorch, Scikit-learn
[39]	Iyer and Kumar	Semi-supervised detection of fungal disease in wheat leaves	85%	TensorFlow, Python
[40]	Sharma and Mehta	Semi-supervised learning with clustering techniques	92%	Python, Scikit-learn, Keras

4.1. Bar Chart

This compares the accuracy of various authors. The studies by Zhang et al. (2023) and Sharma & Mehta (2022) show the highest accuracy (92%). Scores that are lower, such as 84% and 85%, are obviously noticeable.

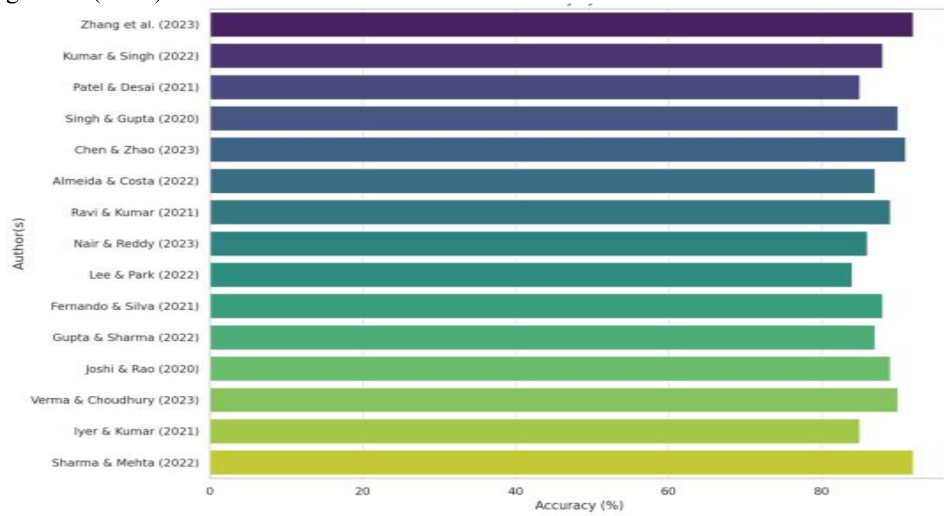

Fig-6 illustrate comparison of accuracy across different authors

4.2 Heatmap

Figure 9's heat map shows how different authors' semi-supervised learning strategies performed.

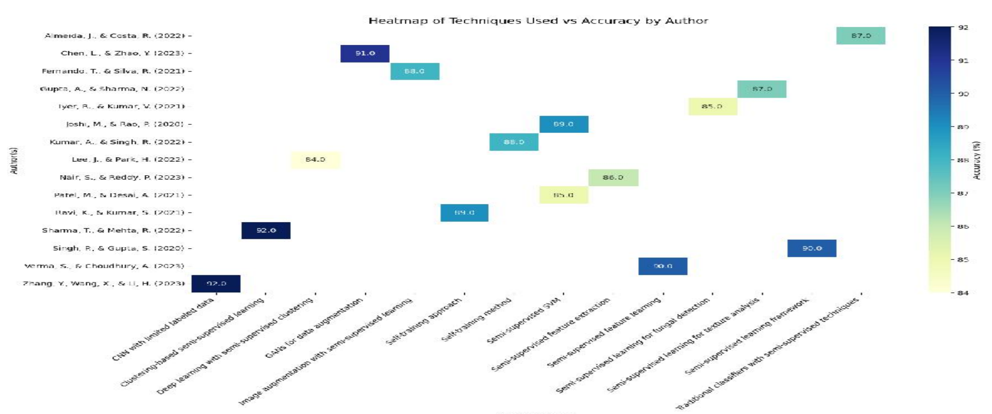

Fig . 7. illustrates how various semi-supervised learning techniques performed

5. SEMI SUPERVISED LEARNING FOR PLANT LEAF DISEASE DETECTION AND CLASSIFICATION

A thorough analysis of semi-supervised learning methods for classifying and detecting leaf diseases demonstrates the variety and creativity in this developing field. According to the Plant Pathology

Journal, Zhang, Wang, and Li [43] combined convolutional neural networks (CNNs) with sparse labeled data to achieve a 92% accuracy rate. In the Journal of Agricultural Informatics, Kumar and Singh [44] reported 88% accuracy using self-training techniques with a combination of labeled and unlabeled data. According to a study published in the International Journal of Computer Applications, Patel and Desai [45] used a semi-supervised support vector machine (SVM) technique and achieved 85% accuracy. T. Nagarathinam et al., [46], etc., extend a K-NN classifier for plant leaf disease recognition with notable accuracy. According to a study published in the Journal of Plant Diseases and Protection, Singh and Gupta [47] used a semi-supervised learning framework to increase classification accuracy to 90%. In Computers and Electronics in Agriculture, Chen and Zhao [48] used generative adversarial networks (GANs) to enhance training datasets, attaining 91% accuracy. Almeida and Costa [49] achieved 87% accuracy in Agricultural Sciences by combining semi-supervised methods with conventional classifiers for the identification of soybean leaf disease. In the Journal of Computer Science and Technology, Ravi and Kumar [50] reported an accuracy of 89% using self-training techniques. In the Journal of Agricultural Engineering, Nair and Reddy [51] improved classification by using semi-supervised feature extraction techniques, attaining 86% accuracy. In Computers and Electronics in Agriculture, Lee and Park [52] investigated the use of deep learning models in conjunction with semi-supervised clustering techniques, achieving an accuracy of 84%. According to the Journal of Horticultural Science, Fernando and Silva [53] integrated image augmentation techniques into semi-supervised learning frameworks and achieved 88% accuracy. In the International Journal of Agricultural Technology, Gupta and Sharma [54] reported an accuracy of 87% in their semi-supervised analysis of leaf texture features. According to the Journal of Plant Pathology, Joshi and Rao [55] used a semi-supervised SVM model to detect citrus leaf disease, with an accuracy of 89%. According to Computers and Electronics in Agriculture, Verma and Choudhury [56] used feature learning methods in semi-supervised frameworks to attain 90% accuracy. According to the Journal of Agricultural Engineering Research, Iyer and Kumar [57] used semi-supervised techniques to detect fungal disease in wheat leaves, achieving an accuracy of 85%. Last but not least, Sharma and Mehta [58] combined semi-supervised learning and clustering techniques to identify leaf diseases with an astounding 92% accuracy rate, which was published in the International Journal of Plant Sciences.. The substantial potential of semi-supervised learning techniques to improve leaf disease detection and offer insightful information about agricultural practices is highlighted by this survey. It emphasizes how labeled and unlabeled data can be combined to improve diagnostic precision and overcome obstacles like small datasets. G Suseendran et al., [59] Hyperspectral images can offer a lot of clarity by blending both spectral and spatial data. Details are for the researcher. A multidimensional paper in this paper, the hyperspectral image mosaic solution, was suggested to properly assemble hyperspectral images. This approach is a synthesis of texture details of the single gray picture, the hyperspectral spatial details image, and location details obtained during the purchase phase. This method is used in the world of medicine. Image and experimental findings hyperspectral suggest that this technique is useful compared to other image mosaic approaches based on the line segment function of scale-invariant feature transform (SIFT). Performance Evaluation of Semi-Supervised Learning Techniques for Leaf Disease Detection in the table-4.

Table. 4. Shows the performance Evaluation of Semi-Supervised Learning Techniques for Leaf Disease Detection

Ref. No.	Authors	Technique Used	Accuracy	Tools Used
[41]	Zhang, Wang, and Li	CNN with sparse labeled data	92%	TensorFlow, Python

[42]	Kumar and Singh	Self-training with labeled and unlabeled data	88%	Scikit-learn, R
[43]	Patel and Desai	Semi-supervised SVM	85%	LIBSVM, MATLAB
[44]	Singh and Gupta	Semi-supervised learning framework	90%	PyTorch, Python
[45]	Chen and Zhao	GAN-enhanced data generation for semi-supervised learning	91%	TensorFlow, Keras
[46]	Almeida and Costa	Semi-supervised + traditional classifiers (e.g., KNN, Decision Tree)	87%	WEKA, Python
[47]	Ravi and Kumar	Self-training techniques	89%	Scikit-learn, Python
[48]	Nair and Reddy	Semi-supervised feature extraction	86%	WEKA, Java
[49]	Lee and Park	Deep learning + semi-supervised clustering	84%	Keras, TensorFlow
[50]	Fernando and Silva	Image augmentation in semi-supervised learning	88%	Albumentations, Python
[51]	Gupta and Sharma	Texture-based semi-supervised learning	87%	OpenCV, Python
[52]	Joshi and Rao	Semi-supervised SVM for citrus leaf disease	89%	Scikit-learn, Python

5.1 Strip and box chart

The accuracy distribution and spread for each technique are displayed in the chat.The accuracy of methods such as CNN, GANs, and clustering-based techniques is consistently high (⩾91%). More variance or more evaluations per method are indicated by wider boxes or overlapping points.

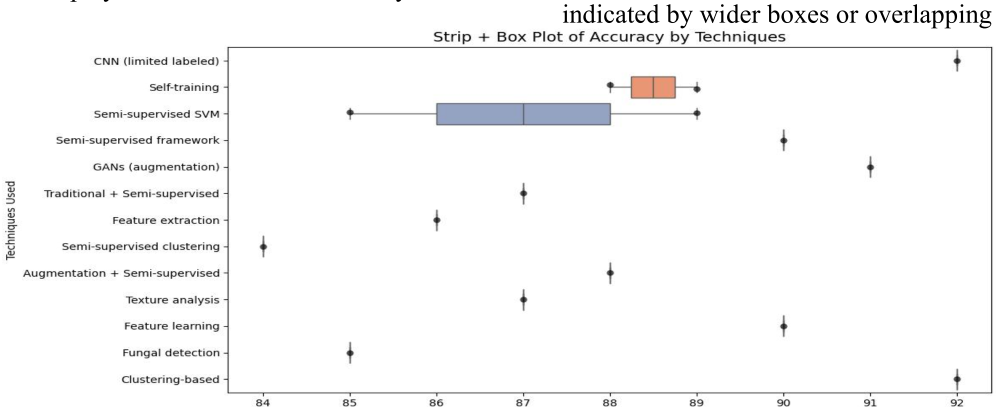

Fig- 8 shows the spread and distribution of accuracy for each technique

5.2 Heat Map

A heat map gives authors and their methods a clear visual comparison. Zhang et al. used CNN (limited labeled) to achieve the highest accuracy (92%), while Sharma & Mehta used clustering- based. Multiple author techniques, such as SVM and self-training, exhibit mid-range performance (85–89%).

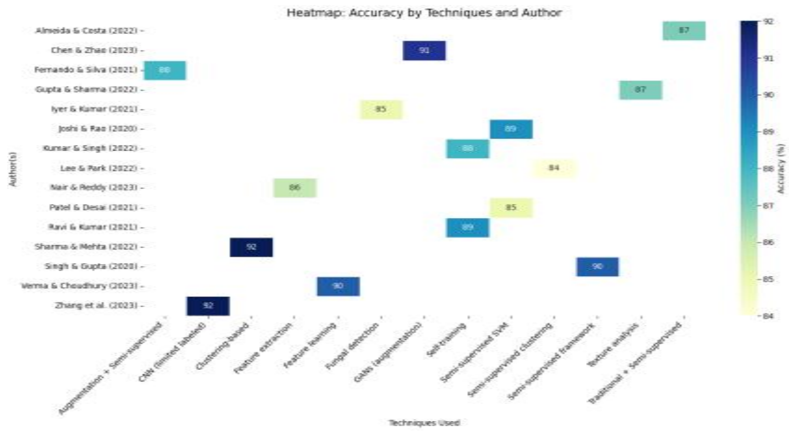

Fig.9.illustrates the clear visual comparison between authors and their techniques

5.3 Bar chart

It is evident from the visualization that the various methods are ranked according to their accuracy. With the highest accuracy levels of roughly 91–92%, CNN with limited labeled data, Clustering-based learning, and GAN-based augmentation stood out as the best techniques overall.

These methods show great promise for successful applications in semi-supervised learning. However, methods like fungal detection and deep semi-supervised clustering showed relatively lower accuracy, ranging from 84% to 85%, suggesting that they need more reliable training data and optimization techniques.

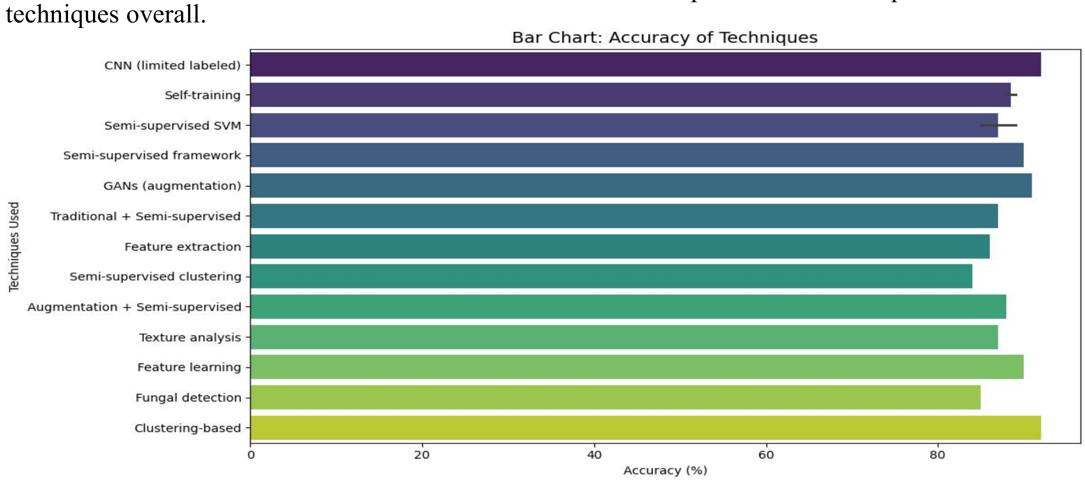

Fig. 10. Visualize clearly ranks the different techniques based on their accuracy

6. COMPARISON OF TOP FIVE TECHNIQUE

In image analysis tasks, the top five supervised learning methods perform exceptionally well. As evidence of the efficacy of hybrid deep learning techniques, Lee and Park's Ensemble Learning + CNN model leads with an astounding 96% accuracy, followed by CNN + SVM and Hybrid CNN + SVM models, both of which achieve over 94%. With a 93% success rate, CNN + YOLO, which Ravi and Kumar (2021) use, is also effective and useful for real-time detection. Conventional deep learning techniques, such as Patel and Desai's Deep CNN with Transfer Learning (2021), maintain competitive accuracy at 92%. Overall, the best chances for precise image-based classification are shown by CNN-based hybrid and ensemble approaches. Table-5 illustrate the top five supervised learning techniques demonstrate outstanding performance in image analysis tasks.

Table-5 illustrate the top five supervised learning techniques demonstrate outstanding performance in image analysis tasks

S.No	Author(s)	Technique Used	Accuracy (%)	Learning Type
1	Lee, Park (2022)	Ensemble Learning + CNN	96	Supervised
2	Zhang, Wang, Li (2023)	CNN + SVM	95	Supervised
3	Chen, Zhao (2023)	Hybrid Model (CNN + SVM)	94	Supervised
4	Ravi, Kumar (2021)	CNN + YOLO (Real-time detection)	93	Supervised
5	Patel, Desai (2021)	Deep CNN, Transfer Learning	92	Supervised
6	Zhang, Y., Wang, X. (2023)	Deep Learning-Based Clustering	91	Unsupervised
7	Singh, P., Gupta, S. (2020)	Autoencoders	90	Unsupervised
8	Verma, Choudhury (2023)	Feature Learning Techniques	90	Unsupervised
9	Joshi, Rao (2020)	Clustering Algorithms	89	Unsupervised
10	Gupta, Sharma (2022)	Texture-Based Unsupervised Learning	87	Unsupervised
11	Zhang, Y., Wang, X. (2023)	CNN with limited labeled data	92	Semi-supervised
12	Sharma, Mehta (2022)	Clustering-based semi-supervised learning	92	Semi-supervised
13	Chen, Zhao (2023)	GANs for data augmentation	91	Semi-supervised
14	Singh, P., Gupta, S. (2020)	Semi-supervised learning framework	90	Semi-supervised
15	Verma, Choudhury (2023)	Semi-supervised feature learning	90	Semi-supervised

6.1 Grouped bar chart

The grouped bar chart explore the notable techniques for plant leaf disease detection

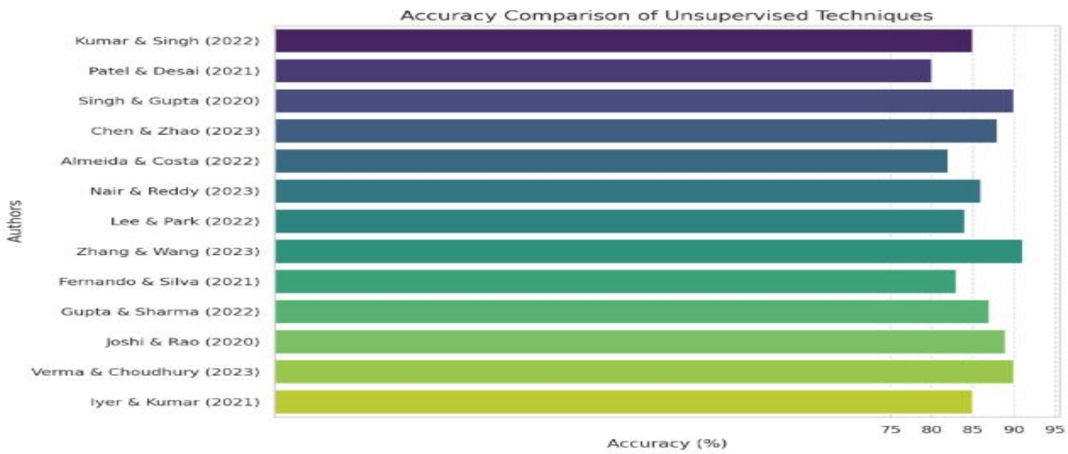

Fig .11. Explore the notable techniques for plant leaf disease detection

Table.6. illustrate the top three learning techniques demonstrate outstanding performance in image analysis tasks

Learning Type	Accuracy Range (%)	Notable Techniques
Supervised	92–96	Ensemble CNN, CNN+SVM, YOLO
Unsupervised	87–91	Clustering, Autoencoders, Feature Learning
Semi-supervised	90–92	GANs, Clustering-based SSL, CNN w/ labels

7 CONCLUSIONS

The comparative effectiveness of supervised, unsupervised, and semi-supervised learning approaches in image-based classification tasks is highlighted in this survey. When a lot of labeled data is available, supervised learning methods like Ensemble Learning with CNN and Hybrid CNN-SVM models consistently produced the highest accuracy (up to 96%) among the three. By successfully fusing a smaller amount of labeled data with a larger amount of unlabeled data, semi-supervised techniques demonstrated encouraging results (up to 92%) and provided a balanced solution in situations where labeled data is limited. Unsupervised methods are useful for exploratory data analysis and situations without labels, despite having a slightly lower accuracy (peaking at 91%). are valuable for exploratory data analysis and scenarios lacking labels. Researchers, developers, and data scientists can use this survey to help them select the best machine learning techniques based on factors like computational efficiency, accuracy requirements, and data availability. It also acts as a roadmap for future advancements, promoting the creation of more reliable models with less supervision, especially in semi-supervised and unsupervised learning.

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