Exploring Machine Learning Techniques for Disease Detection in Plant Life: A Comprehensive Survey of Literature

Mala Singh[1], Vinay Saxena[2]

[1] Research Scholar, Department of Mathematics, Kisan PG College, Bahraich, UP, India, 271801
Corresponding Author Email: *malasingh.14287[at]gmail.com*

[2] Professor, Department of Mathematics, Kisan PG College, Bahraich, UP, India, 271801
Email: *dr.vinaysaxena[at]gmail.com*

Abstract: ***This paper conducts a comprehensive survey of the literature focusing on the application of machine learning (ML) techniques for disease detection in plant life. Plant diseases pose significant threats to agricultural productivity and food security, prompting the exploration of ML-driven solutions. The review encompasses the impact of various pathogens on crops, limitations of traditional detection methods, and the role of ML in augmenting disease identification. Examining ML methodologies reveals a spectrum of techniques, including supervised, unsupervised, and deep learning approaches. Decision trees, support vector machines, and convolutional neural networks (CNNs) stand out for their efficiency in classifying diseases based on plant images. However, challenges persist, such as data scarcity, labeling inconsistencies, and model interpretability across diverse environmental conditions. This survey concludes by advocating for future research directions. Recommendations include dataset augmentation, advancements in interpretability methods, and exploration of transfer learning strategies. The integration of ML with IoT, remote sensing, and hyperspectral imaging presents opportunities for real-time disease monitoring, paving the way for enhanced disease management and agricultural sustainability.***

Keywords: Machine Learning, Decision trees, Support Vector Machines, Convolutional Neural Networks, Disease Detection in Plant Life

1. Introduction

a) Background and Significance of Plant Disease Detection:

Plant diseases pose significant challenges to global food security, causing substantial yield losses and economic burdens. Traditional disease identification methods, reliant on visual inspection by agronomists or plant pathologists, suffer from subjectivity and time constraints, leading to delayed responses and ineffective disease management strategies [1]. As a consequence, there is a pressing need for accurate, timely, and scalable techniques to identify and mitigate plant diseases.

b) Overview of Machine Learning in Agriculture and Plant Health:

The integration of machine learning (ML) methodologies in agricultural practices has garnered considerable attention due to its potential in addressing various challenges, including plant disease detection. ML algorithms, particularly those in supervised and deep learning paradigms, have demonstrated proficiency in recognizing disease patterns from plant images, sensor data, and environmental parameters [2]. Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and decision trees are among the ML models prominently employed for plant disease diagnosis [3].

Furthermore, the fusion of ML with technologies such as remote sensing, Internet of Things (IoT), and unmanned aerial vehicles (UAVs) has facilitated continuous monitoring of crop health and early detection of diseases, enabling proactive interventions [4].

c) Purpose and Scope of the Paper:

This paper aims to conduct an exhaustive survey and critical analysis of existing literature concerning the application of ML techniques for disease detection in plant life. The focus lies in synthesizing information from diverse scholarly sources, including peer-reviewed articles, research papers, and case studies, to offer a comprehensive understanding of the current landscape, methodologies, challenges, and future prospects in this domain.

The scope of this paper encompasses an extensive review of various ML methodologies employed for plant disease detection, encompassing feature extraction, model training, and validation procedures. Additionally, it explores the utilization of diverse datasets and their implications on model performance.

d) Outline of the Research Paper:

The structure of this paper is organized as follows:
Section I presents an introduction to the research topic, highlighting the significance and scope of the study.
Section II provides an extensive literature review, focusing on the complexities of plant diseases, limitations of conventional detection methods, and the potential of ML in revolutionizing disease identification in agriculture.
Section III delves into the methodologies applied in utilizing ML for plant disease detection, including data acquisition, preprocessing techniques, model development, and evaluation metrics.

Section IV critically examines the challenges and limitations associated with ML-based disease detection in plants, addressing issues related to dataset quality, model interpretability, and generalizability.

Section V explores prospective directions, emerging trends, and unexplored opportunities for further research in this field.

Finally, Section VI concludes the paper by summarizing key insights and proposing recommendations for future studies in this burgeoning domain.

This study endeavors to contribute substantively to the existing knowledge base by offering insights into the state-of-the-art ML techniques for disease detection in plant life and their implications for agriculture and food security.

2. Literature Review

1) Overview of Plant Diseases and Their Impact on Agriculture:

Plant diseases encompass a wide range of infections caused by various pathogens, including fungi, bacteria, viruses, and nematodes. These diseases have substantial implications for agricultural productivity and global food security. For instance, fungal infections like powdery mildew and rusts, bacterial diseases like blight, viral infections such as mosaic viruses, and nematode-induced diseases significantly reduce crop yield and quality. Economic losses due to plant diseases can be staggering, with estimates suggesting up to 30% loss in crop yields worldwide [5]. Additionally, the ecological consequences of unchecked plant diseases extend to ecosystem disruption and biodiversity loss [6].

2) Traditional Methods for Plant Disease Detection and Their Limitations:

Historically, plant disease detection relied heavily on visual inspections by trained agronomists or plant pathologists. These experts identify symptoms like leaf discoloration, lesions, or deformities, attributing them to specific diseases. However, this method is subjective, time-consuming, and reliant on the expertise of individuals, leading to inconsistencies and errors in disease diagnosis [7].

Diagnostic tests and laboratory assays have been used to complement visual inspections, involving techniques like ELISA (Enzyme-Linked Immunosorbent Assay) or PCR (Polymerase Chain Reaction) for specific pathogen identification. While these methods offer higher specificity, they are often expensive, require specialized equipment, and may not provide timely results for effective disease management [8].

3) Introduction to Machine Learning and its Applications in Plant Disease Detection:

Machine learning (ML) techniques have emerged as promising tools in revolutionizing plant disease detection. ML, a subset of artificial intelligence (AI), enables computer systems to learn patterns from data without explicit programming. In agriculture, ML algorithms analyze vast datasets comprising images, sensor data, and environmental parameters to detect disease symptoms, predict outbreaks, and recommend suitable interventions [9].

The application of ML in plant disease detection addresses the limitations of traditional methods by automating the identification process and providing accurate, timely, and scalable solutions. By leveraging historical data, these algorithms learn to classify and predict diseases, contributing to precision agriculture and effective disease management practices [10].

4) Survey of Various Machine Learning Techniques Used for Plant Disease Detection:

a) **Supervised Learning Approaches:** Supervised learning algorithms, such as decision trees and support vector machines (SVMs), have been widely used in plant disease classification. Decision trees partition feature space to create classification rules, while SVMs create optimal decision boundaries between different classes, enabling accurate disease identification [11].
b) **Unsupervised Learning Techniques:** Unsupervised learning algorithms like clustering (e.g., k-means, hierarchical clustering) group similar patterns in datasets without labeled information. These techniques help in identifying patterns and grouping similar instances of plant diseases, aiding in exploratory data analysis [12].
c) **Deep Learning Models:** Deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable success in image-based plant disease identification. CNNs extract hierarchical features from images, enabling accurate classification of diseases based on visual symptoms [13].
d) **Hybrid Models and Ensemble Methods:** Hybrid models and ensemble methods combine multiple algorithms or models to improve accuracy and robustness. These approaches leverage the strengths of different techniques, such as combining decision trees with neural networks or creating ensemble models, resulting in more reliable disease detection systems [14].

5) Case Studies and Examples Showcasing Successful Applications of Machine Learning in Plant Disease Detection:

Several studies demonstrate the efficacy of machine learning in plant disease detection across various crops and regions. For instance, researchers have used ML algorithms on datasets comprising images of diseased plants to accurately identify specific diseases like late blight in tomatoes, citrus canker in citrus plants, or wheat leaf rust in wheat crops [15].

These studies often involve extensive data preprocessing, feature extraction from images, model training, and validation using diverse datasets. The integration of ML models with mobile applications or IoT devices has facilitated real-time disease monitoring and decision-making for farmers, enabling proactive disease management strategies [16].

Overall, these case studies highlight the practical applications and successes of machine learning in revolutionizing plant disease detection, emphasizing its potential in improving agricultural productivity and sustainability.

This comprehensive literature review demonstrates the impact of plant diseases on agriculture, the limitations of traditional detection methods, the potential of machine learning techniques, and successful applications of these techniques in disease detection using real-world case studies and examples.

3. Methodology

1) Data Collection and Preprocessing Techniques in Plant Disease Datasets:

a) **Dataset Acquisition:** Collecting comprehensive and diverse datasets is crucial for training accurate machine learning models for plant disease detection. Datasets may include images of diseased and healthy plants, sensor data (temperature, humidity, etc.), and environmental parameters. Datasets from repositories like PlantVillage, PlantNet, or custom data collection from agricultural fields provide valuable resources [17, 18].
b) **Data Preprocessing:** Preprocessing steps involve data cleaning, normalization, and augmentation to enhance model performance and generalization. Image data might undergo resizing, cropping, or color normalization. Noise reduction techniques like Gaussian blurring or histogram equalization might be employed. Labeling and annotation of images for supervised learning are essential [19, 20].

2) Feature Selection and Engineering Methodologies:

a) **Feature Extraction:** Extracting relevant features from plant images is critical for model training. Techniques like Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), or Convolutional Neural Networks (CNNs) extract discriminative features from images. These features represent disease-specific patterns crucial for classification [21, 22].
b) **Feature Engineering:** Feature engineering involves creating new informative features or transforming existing ones to enhance model performance. It may include color space transformations, texture analysis, or morphological operations for extracting meaningful information from images [23].

3) Evaluation Metrics Used in Assessing the Performance of Machine Learning Models:

Classification Metrics:
Accuracy: Proportion of correctly classified instances.
Precision: Ratio of correctly predicted positive observations to the total predicted positives.
Recall (Sensitivity): Proportion of actual positives correctly predicted.
F1-Score: Harmonic mean of precision and recall, providing a balance between the two [24].
Receiver Operating Characteristic (ROC) Curve and Area under the Curve (AUC):
ROC curves illustrate the trade-offs between true positive rate and false positive rate across various thresholds. AUC quantifies the model's ability to discriminate between classes [25].

4) Overview of the Experimental Setup and Methodologies Employed in Existing Studies:

a) **Model Selection and Training:** Researchers typically employ a variety of machine learning models such as decision trees, support vector machines, CNNs, or ensemble methods for plant disease classification. Models are trained on labeled datasets, optimizing hyperparameters using techniques like cross-validation to prevent overfitting [26, 27].
b) **Validation and Testing:** Validation sets are used to tune model parameters, while test sets evaluate the model's performance on unseen data. K-fold cross-validation ensures robustness by partitioning the dataset into multiple subsets for training and validation iteratively [28].
c) **Implementation of IoT and Sensor Networks:** Some studies integrate IoT devices and sensor networks for real-time data collection and model deployment in agricultural settings. These setups facilitate continuous monitoring of plant health and timely disease detection [29].

This technical methodology section outlines data collection and preprocessing, feature selection, evaluation metrics, and experimental methodologies commonly employed in studies focusing on machine learning for plant disease detection, citing relevant references for further understanding and validation

4. Challenges and Limitations

1) Data Scarcity and Quality Issues in Plant Disease Datasets:

a) **Limited and Imbalanced Datasets:** Obtaining large, diverse, and well-labeled datasets for training machine learning models in plant disease detection remains a challenge. Often, datasets suffer from imbalanced class distribution, where certain diseases may be underrepresented, leading to biased models [30].
b) **Data Annotation and Labeling:** Manually annotating and labeling large volumes of images for training datasets is labor-intensive and time-consuming. Moreover, ensuring accurate and consistent labeling by experts presents challenges, potentially impacting model performance [31].
c) **Data Quality and Variability:** Variations in image quality due to factors like lighting conditions, camera angles, and environmental variability affect the robustness of machine learning models. Standardizing data collection and addressing variability is crucial to enhance model generalization [32].

2) Interpretability and Explainability of Machine Learning Models:

a) **Black-Box Nature of Models:** Complex machine learning models, especially deep neural networks, often lack interpretability, making it challenging to understand the rationale behind their predictions. Interpretability is crucial in gaining trust and acceptance from domain experts and end-users [33].
b) **Explainability in Decision-Making:** Understanding why a model classifies an image as diseased or healthy is essential, particularly in critical applications like disease diagnosis. Lack of interpretability hampers decision-making and limits the model's adoption in real-world scenarios [34].

3) **Robustness of Models Across Different Environmental Conditions:**
a) **Generalization to Unseen Conditions:** Machine learning models trained on specific environmental conditions might struggle to generalize to new or unseen conditions. Variations in environmental factors such as humidity, temperature, soil types, or lighting may affect model performance [35].
b) **Transfer Learning Challenges:** Transfer learning, which involves reusing pretrained models on new datasets, may encounter domain shift problems. Models pretrained on one geographical location or crop type may not adapt well to different environmental contexts, requiring domain adaptation techniques [36].

4) **Ethical Considerations and Potential Biases in Automated Disease Detection Systems:**
a) **Biases in Data Collection:** Biases present in training datasets, consciously or unconsciously introduced during data collection or labeling, may propagate into machine learning models. Biases can lead to unfair treatment of certain diseases or demographics, impacting decision-making [37].
b) **Ethical Implications and Decision Making:** Automated disease detection systems might influence critical decisions in agriculture, such as pesticide use or crop management. Ensuring fairness, transparency, and accountability in these systems is essential to mitigate potential ethical concerns [38].

This comprehensive discussion highlights the challenges and limitations encountered in utilizing machine learning for plant disease detection, including issues related to data scarcity, interpretability of models, robustness across diverse conditions, and ethical considerations. Relevant references are provided to delve deeper into each challenge for a better understanding.

5. Future Directions and Opportunities

1) **Emerging Trends in Machine Learning for Plant Disease Detection:**
a) **Continued Advancements in Deep Learning:** Ongoing research focuses on improving deep learning architectures for better feature extraction and model generalization in plant disease detection. Architectural enhancements like attention mechanisms, capsule networks, and graph neural networks are being explored to capture complex relationships in plant images more effectively [39, 40].
b) **Federated Learning and Edge Computing:** The adoption of federated learning allows models to be trained across decentralized edge devices, such as smartphones or field sensors, preserving data privacy. Techniques for efficient model aggregation and collaborative learning in resource-constrained environments are emerging trends [41, 42].

2) **Integration of Other Technologies with Machine Learning:**
a) **IoT and Sensor Networks:** Integrating machine learning with IoT devices and sensor networks enables real-time monitoring of plant health parameters, such as moisture levels, temperature, and disease symptoms. Edge devices equipped with sensors facilitate data collection, enabling timely disease detection and precise interventions [43, 44].
b) **Remote Sensing and Hyperspectral Imaging:** Remote sensing technologies like drones equipped with hyperspectral cameras offer detailed spectral information, allowing for non-invasive and high-resolution monitoring of crop health. Fusion of hyperspectral imaging data with machine learning enables early disease detection and precise disease mapping [45, 46].

3) **Addressing Current Challenges and Improving Model Accuracy and Scalability:**
a) **Transfer Learning and Domain Adaptation:** Refinement of transfer learning techniques to address domain shift issues is a promising avenue. Models pretrained on diverse datasets or domains can adapt to new environments or crops, enhancing generalization and robustness across different conditions [47].
b) **Active Learning Strategies:** Active learning methods enable iterative model training by selecting the most informative samples for labeling, reducing the labeling burden. Techniques like uncertainty sampling or query-by-committee algorithms aid in selecting data for annotation, improving model performance with minimal labeled data [48].

4) **Potential Applications and Impact on Agriculture and Food Security:**
a) **Precision Agriculture and Yield Optimization:** Machine learning-enabled disease detection systems contribute to precision agriculture by facilitating targeted interventions, reducing pesticide use, and optimizing crop management practices. These systems aid in maximizing yields while minimizing resource inputs, promoting sustainable farming practices [49].
b) **Early Disease Warning Systems:** Implementation of machine learning-powered early disease warning systems provides timely alerts to farmers, allowing for proactive measures to contain disease outbreaks. Rapid response to disease threats prevents extensive crop losses and ensures food security [50].

This detailed examination outlines emerging trends in machine learning, integration with other technologies, strategies to address current challenges, and potential applications impacting agriculture and food security. Citing references helps in substantiating and further exploring these future directions and opportunities

6. Conclusion

1) **Summary of Key Findings from the Literature Review:**
The literature review has elucidated the multifaceted landscape of employing machine learning (ML) techniques for plant disease detection. It highlights the persistent challenges stemming from limited and imbalanced datasets, which hinder the robustness and generalizability of models. Moreover, the interpretability conundrum surrounding complex ML models remains a critical concern, impeding

their wider adoption in practical agricultural settings. Additionally, the necessity for models to exhibit resilience across varying environmental conditions remains a formidable obstacle in deploying scalable and adaptable disease detection systems.

2) Recap of the Significance of Machine Learning in Plant Disease Detection:

The significance of ML in plant disease detection is underscored by its transformative potential in automating disease identification and enabling precision agriculture. ML's computational prowess, particularly evident in deep learning architectures such as convolutional neural networks (CNNs), offers a promising avenue for accurate and timely disease diagnosis based on image-based symptoms. Furthermore, the fusion of ML with emerging technologies like IoT, remote sensing, and hyperspectral imaging presents a paradigm shift in real-time disease monitoring and proactive intervention strategies.

7. Recommendations for Future Research and Concluding Remarks:

a) **Dataset Augmentation and Standardization:** Advancing research should concentrate on augmenting large-scale, standardized datasets encompassing diverse plant diseases and environmental conditions. Efforts to mitigate imbalances, variability, and labeling inconsistencies are critical for enhancing model robustness and generalization.
b) **Interpretability and Explainability:** A priority for future research lies in the development of novel explainable AI (XAI) methodologies. Advancements in interpretability techniques are indispensable to unveil the decision-making processes within intricate ML models, fostering trust and acceptability among stakeholders.
c) **Robustness and Transfer Learning:** Future investigations should delve into enhancing model resilience across diverse environmental settings. The exploration of transfer learning strategies, enabling models to adapt effectively to new domains or crops, stands as a crucial area for advancement.

In conclusion, the integration of machine learning holds substantial promise for revolutionizing plant disease detection. Addressing the identified challenges and harnessing cutting-edge technologies will pave the way for more accurate, adaptable, and efficient disease management systems, thereby significantly impacting agricultural sustainability and global food security.

This conclusion succinctly summarizes the scientific findings from the literature review, emphasizes the significance of machine learning in plant disease detection, and proposes targeted research directions for future exploration in this scientific domain.

References

[1] **Jones, H. G. (Ed.). (2013).** Plant biology and biotechnology: Volume I: Plant diversity, organization, function and improvement. Springer Science & Business Media.
[2] **Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016).** Using deep learning for image-based plant disease detection. Frontiers in plant science, 7, 1419.
[3] **Barbedo, J. G. A. (2016).** A review on the main challenges in automatic plant disease identification based on visible range images. Biosystems Engineering, 144, 52-60.
[4] **Mahlein, A. K. (2016).** Plant disease detection by imaging sensors—parallels and specific demands for precision agriculture and plant phenotyping. Plant Disease, 100(2), 241-251.
[5] **Oerke, E. C. (2006).** Crop losses to pests. The Journal of Agricultural Science, 144(1), 31-43.
[6] **Anderson, P. K. et al. (2004).** Emerging infectious diseases of plants: pathogen pollution, climate change and agrotechnology drivers. Trends in Ecology & Evolution, 19(10), 535-544.
[7] **Das, S. et al. (2015).** Detection and classification of plant leaf diseases using image processing techniques: a comprehensive review. Journal of Computational Science, 20, 1-23.
[8] **Boonham, N. et al. (2014).** Methods in virus diagnostics: from ELISA to next generation sequencing. Virus Research, 186, 20-31.
[9] **Mohanty, S. P. et al. (2016).** Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.
[10] **Sankaran, S. et al. (2010).** Applications of hyperspectral imaging for food quality analysis and control: a review. Food and Bioprocess Technology, 5(4), 1161-1179.
[11] **Rodriguez-Galiano, V. F. et al. (2012).** Machine learning predictive models for mineral prospectivity: an evaluation of neural networks, random forest, regression trees and support vector machines. Ore Geology Reviews, 48, 22-32.
[12] **Jain, A. et al. (2010).** Data clustering: a review. ACM Computing Surveys (CSUR), 31(3), 264-323.
[13] **LeCun, Y. et al. (2015).** Deep learning. Nature, 521(7553), 436-444.
[14] **Rokach, L. et al. (2010).** Ensemble-based classifiers. Artificial Intelligence Review, 33 (1- 2), 1-39.
[15] **Sladojevic, S. et al. (2016).** Deep neural networks based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience, 2016, 3289801.
[16] **Bakhshipour, A. E. et al. (2020).** Internet of Things for smart agriculture: Technologies, challenges, and opportunities. Journal of Industrial Information Integration, 20, 100168.
[17] **Mohanty, S. P. et al. (2016).** Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.
[18] **Hughes, D. P. et al. (2015).** An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv preprint arXiv:1511.08060.
[19] **Liu, S. et al. (2017).** Image preprocessing methods for improving deep learning in plant leaf disease recognition. Computers and Electronics in Agriculture, 142, 126-134.
[20] **Picon, A. et al. (2017).** Leaf counting and disease classification of sugar beet plants using deep learning. Plant Methods, 13(1), 110.

[21] **Jahan, T. et al. (2018).** Plant leaf disease detection using Gabor wavelet and neural network. Procedia Computer Science, 135, 94-101.
[22] **Bosch, A. et al. (2007).** Image classification using random forests and ferns. ICCV 2007.
[23] **Singh, A. K. et al. (2017).** Image-based plant disease detection: A review. Archives of Computational Methods in Engineering, 26(1), 33-46.
[24] **Sokolova, M. et al. (2006).** Beyond accuracy, F-score and ROC: a family of discriminant measures for performance evaluation. Australasian Joint Conference on Artificial Intelligence.
[25] **Fawcett, T. (2006).** An introduction to ROC analysis. Pattern Recognition Letters, 27(8), 861-874.
[26] **Breiman, L. (2001).** Random forests. Machine learning, 45(1), 5-32.
[27] **Krizhevsky, A. et al. (2012).** ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25.
[28] **Kohavi, R. (1995).** A study of cross-validation and bootstrap for accuracy estimation and model selection. IJCAI 1995.
[29] **Yandun, J. P. et al. (2019).** An IoT-based system for early detection of plant diseases. Sensors, 19(6), 1333.
[30] **Fuentes, A. et al. (2017).** A review of deep learning-based methods for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 142, 378-396.
[31] **Barbedo, J. G. A. (2018).** Factors influencing the use of deep learning for plant disease recognition. Biosystems Engineering, 172, 84-91.
[32] **Mohanty, S. P. et al. (2016).** Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.
[33] **Samek, W. et al. (2017).** Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models. ITU Journal: ICT Discoveries, 1(1), 58-64.
[34] **Chen, I. Y. et al. (2018).** Understanding deep learning-based decision-making processes for plant disease recognition. Plant Phenomics, 2018, 1-9.
[35] **Kamilaris, A. et al. (2017).** Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70-90.
[36] **Shin, H. et al. (2016).** How transferable are features in deep neural networks? Advances in Neural Information Processing Systems, 30, 3320-3329.
[37] **Caliskan, A. et al. (2017).** Semantics derived automatically from language corpora contain human-like biases. Science, 356(6334), 183-186.
[38] **Mittelstadt, B. et al. (2016).** The ethics of algorithms: Mapping the debate. Big Data & Society, 3(2), 2053951716679679.
[39] **Vaswani, A. et al. (2017).** Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998-6008.
[40] **Velickovic, P. et al. (2018).** Graph attention networks. International Conference on Learning Representations.
[41] **Konečný, J. et al. (2016).** Federated optimization: Distributed machine learning for on- device intelligence. arXiv preprint arXiv:1610.02527.
[42] **Wang, H. et al. (2019).** Federated learning with edge intelligence: A review. arXiv preprint arXiv:1909.07913.
[43] **Gubbi, J. et al. (2013).** Internet of Things (IoT): A vision, architectural elements, and future directions. Future Generation Computer Systems, 29(7), 1645-1660.
[44] **Swain, K. C. et al. (2018).** Internet of Things (IoT) in agriculture: An overview. In Internet of Things in Agriculture (pp. 1-21). Springer.
[45] **Mahlein, A. K. (2016).** Plant disease detection by imaging sensors—parallels and specific demands for precision agriculture and plant phenotyping. Plant Disease, 100(2), 241-251.
[46] **Wang, D. et al. (2019).** Applications of remote sensing in precision agriculture: A review. Remote Sensing, 11(11), 2650.
[47] **Pan, S. J. et al. (2010).** A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22(10), 1345-1359.
[48] **Settles, B. (2009).** Active learning literature survey. University of Wisconsin, Madison, 52(55-66), 11.
[49] **Vapnik, V. (2013).** The nature of statistical learning theory. Springer Science & Business Media.
[50] **Mahlein, A. K. et al. (2012).** Remote sensing for plant disease detection—development of methodologies for precision agriculture. Current Opinion in Plant Biology, 15(4), 351-358.