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A Survey on Aeroponic System with Automated Nutrition and Disease Analysis

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Abstract*: The study introduces an innovative aeroponic system approach that automates nutrient delivery and integrates machine learning for disease analysis. The system leverages sensors to monitor critical environmental parameters, ensuring precise nutrient administration. By employing image processing and machine learning techniques, it provides real-time health diagnostics, identifying diseases and nutrient deficiencies early. Designed for scalability and cost-effectiveness, The system offers a robust solution for both small-scale and commercial agriculture, improving yields while reducing manual intervention and resource waste. This paper reviews the methodologies, applications, and advancements in automated aeroponic systems*

Keywords: Aeroponics, Automated nutrient delivery, Disease analysis, Machine learning, Image processing, Internet of Things (IoT) Precision agriculture, Sustainability, Deep learning, Real-time monitoring, Nutrient optimization, Crop health diagnostics, Controlled-environment agriculture

I. INTRODUCTION

The global population is projected to exceed 9.7 billion by 2050, demanding a 70% increase in food production to meet the needs of the growing populace. However, the agricultural sector faces numerous challenges, including diminishing arable land, water scarcity, soil degradation, and unpredictable climate conditions. Traditional soil-based farming systems often require intensive labour and are resource-intensive, exacerbating these challenges. Moreover, reliance on conventional farming methods is increasingly unsustainable due to inefficiencies in water and nutrient usage, as well as the vulnerability of crops to diseases and pests.

Aeroponics, a soilless cultivation technique, has emerged as a viable alternative to traditional farming. By delivering nutrient-rich mist directly to the roots of plants, aeroponics optimizes nutrient absorption, minimizes water usage by up to 95%, and eliminates the need for arable land. Furthermore, aeroponics enables year-round cultivation, making it highly suitable for urban and controlled-environment agriculture. Despite these advantages, the widespread adoption of aeroponic systems is hindered by the high degree of manual intervention required to manage nutrient delivery and monitor plant health. Human errors in nutrient administration or delays in disease detection can significantly impact crop yields and resource efficiency. The innovative approach minimizes human intervention, reduces operational costs, and enhances crop productivity, making precision agriculture more accessible to small-scale and commercial farmers alike. Aeroponics aligns with global sustainability goals by promoting resource-efficient farming practices. By leveraging technology to optimize nutrient usage and reduce waste, the system contributes to reducing the environmental impact of agriculture. Furthermore, its adaptability to urban environments positions aeroponics as a critical solution for addressing food security challenges in densely populated areas. This paper presents a comprehensive survey of the methodologies and technologies underpinning the development of automated aeroponic systems. It examines recent advancements in sensor integration, machine learning, and IoT-based agricultural practices, highlighting their potential to revolutionize modern farming.

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II. RESEARCH METHODOLOGY

The studies collectively emphasize the integration of advanced technologies such as machine learning, IoT, and image processing to address challenges in modern agriculture. A significant focus lies in leveraging image-based techniques for plant health monitoring and disease detection. Several studies adopted deep learning models, including convolutional neural networks (CNNs) and advanced architectures like Restructured Deep Residual Dense Networks (RRDN) and MobileNetV2, to classify diseases and monitor plant health. These models demonstrated high accuracy in identifying diseases in tomato leaves and other crops. Attention-based mechanisms, such as RoI-Attention Networks, were particularly effective for segmenting small disease regions. Moreover, techniques like PCA-based feature extraction and GAN-driven data augmentation further enhanced model robustness, enabling the handling of diverse agricultural datasets.

The IoT-based automation has been a key enabler in improving agricultural efficiency. IoT protocols like MQTT and HTTP facilitated real-time data acquisition and monitoring of environmental factors such as temperature, humidity, and nutrient levels in greenhouse and aeroponic systems. The automation of nutrient delivery systems, achieved through sensors (e.g., pH, electrical conductivity) and microcontrollers, ensured precision and reduced manual errors. Studies also incorporated life-cycle assessments (LCA) to evaluate the environmental and economic impacts of automated systems, underscoring the importance of sustainability in modern farming practices

Furthermore, advanced modelling approaches, including Lite-UNet for resource-efficient segmentation and YOLOv7/YOLOv8 for real-time object detection, highlight the role of computational efficiency in scalable implementations. The use of mechanistic models and group-wise transformers to enhance prediction accuracy while maintaining resource efficiency. Tools like Grad-CAM++ further contributed to explainable AI, providing insights into disease classification and ensuring user trust in AI-driven systems. The methodologies across these studies highlight the importance of combining precision technologies, real-time monitoring, and sustainability principles to revolutionize agriculture, particularly in aeroponic and hydroponic farming systems.

III. LITERATURE REVIEW

X. Yang et al. proposed a method using ISC-MRCNN for instance segmentation and APS-DCCNN for classification of plant leaf images. This approach significantly improved detection precision by 1.89% and classification accuracy by 1.59% [1]. While effective in leaf segmentation, its application is limited to plant leaves and lacks generalization to other agricultural components.

M. Agarwal et al. developed a convolutional neural network (CNN) for tomato leaf disease detection, consisting of three convolution layers, three max-pooling layers, and two fully connected layers. Achieving an accuracy of 91.2%, the model outperformed VGG16 and MobileNet [2]. However, it requires large datasets and is computationally intensive.

X. Schmidt Rivera et al. conducted a Life Cycle Assessment (LCA) to evaluate the environmental credentials of aeroponic systems, focusing on energy consumption and greenhouse gas emissions [3]. The study highlighted the environmental benefits of renewable energy integration but identified the high energy cost as a limitation.

C. Zhou et al. introduced a Restructured Deep Residual Dense Network (RRDN) for classifying tomato leaf diseases, achieving a top 1 accuracy of 95% [4]. The model demonstrated adaptability and computational efficiency but was limited to a tomato dataset.

M. S. Farooq et al. reviewed IoT communication protocols like MQTT and HTTP for precision farming in greenhouse agriculture [5]. IoT-based systems significantly enhanced crop yields and resource efficiency. However, the high initial costs were noted as a barrier for small-scale farmers.

Y. Lu et al. proposed a segmentation method based on image contrast optimization to improve the separation of plants and background regions in RGB images [6]. The technique achieved an F1-score of 95% and showed consistent results across various conditions but required optimization for each dataset.

S. Ahmed et al. developed a lightweight deep learning model using MobileNetV2 for tomato leaf disease detection, achieving 99.3% accuracy [7]. This model was computationally efficient and suitable for resource-constrained devices, but its scalability for larger datasets requires further validation.

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G. L. Priya et al. presented an AI-enabled hydroponics system integrating IoT and machine learning for nutrient dispensation and deficiency detection. The system achieved 95% validation accuracy [8] , but its reliance on historical data and hardware constraints limited scalability.

H. S. El-Assiouti et al. proposed Lite-UNet for segmentation and Lite-SRGAN for super-resolution of plant disease images [9]. This approach was resource-efficient and achieved high segmentation accuracy but was constrained by the limited variability in its dataset.

K. Roy et al. developed PCA DeepNet, a hybrid model combining PCA for feature extraction and CNN for tomato leaf disease detection. With a classification accuracy of 99.6% [10], the model relied on GAN-based data augmentation, which increased resource requirements.

A. Sharma et al. designed a controlled environment ecosystem for soilless farming using mechanistic models and neural networ [11]. The system achieved 90% water efficiency and 80% land savings but required high initial investment and technical expertise for maintenance.

G. Y. Moon and J. O. Kim introduced the RoI-Attention Network (RA-Net) for small disease segmentation in crop images [12]. The model improved segmentation accuracy for small regions but lacked applicability to larger and more generalized datasets.

M. Umar et al. utilized an enhanced YOLOv7 model integrated with SimAM and DAiAM mechanisms for multi-disease recognition in tomato plants [13]. The model achieved 98.8% accuracy in real-time conditions but was limited to specific datasets, affecting generalization.

N. Sadek et al. presented an IoT-based automated aeroponics system for greenhouse farming in Egypt. The system demonstrated significant water savings and productivity improvements [14], though its dependency on reliable internet and power posed challenges for implementation in resource-limited areas.

J. Feng et al. combined EfficientNet with group-wise transformers to enhance crop disease detection, achieving over 99% accuracy on multiple datasets [15]. However, the system exhibited limited performance in diverse real-time environments.

L. D. Quach et al. implemented YOLOv8 with Grad-CAM++ for real-time tomato plant monitoring, achieving high classification accuracy while providing explainable AI capabilities [16]. The study highlighted the model's reliance on specific datasets, which may affect its application to broader agricultural contexts.

IV. RESULTS AND DISCUSSION

TABLE 1. Details of technique used by various researchers.

Technique used	Author	Result
ISC-MRCNN for instance segmentation and APS-DCCNN for classification	X. Yang et al. (2020)	Improved detection by 1.89%, classification by 1.59%
CNN with three convolutional layers and data augmentation for tomato leaf disease detection	M. Agarwal et al. (2020)	Average classification accuracy of 91.2%
Restructured Deep Residual Dense Network (RRDN) for tomato leaf disease classification	C. Zhou et al. (2021)	Top-1 accuracy of 95% on the test dataset
IoT protocols (MQTT and HTTP) for precision farming in greenhouses	M. S. Farooq et al. (2022)	Improved crop yield, optimized resources, high cost for small-scale use
Image contrast optimization for plant segmentation in RGB images	Y. Lu et al. (2022)	F1 segmentation accuracy of 95%
MobileNetV2-based lightweight neural network for tomato leaf disease detection	S. Ahmed et al. (2022)	99.3% accuracy with efficient computation
IoT sensors and machine learning integration for hydroponic nutrient optimization	G. L. Priya et al. (2023)	Validation accuracy of 95%
Lite-UNet for segmentation and Lite-SRGAN for super-resolution of plant disease images	H. S. El-Assiouti et al. (2023)	Improved segmentation accuracy, resource-efficient

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PCA-based feature extraction combined with CNN and GANs for tomato leaf disease detection	K. Roy et al. (2023)	Classification accuracy of 99.6%
Mechanistic and neural models for controlled-environment farming systems	A. Sharma et al. (2024)	Water efficiency of 90%, land savings of 80%
RoI-Attention Network (RA-Net) for small disease region segmentation	G. Y. Moon and J. O. Kim (2024)	Improved segmentation accuracy for small regions
YOLOv7 with SimAM and DAiAM mechanisms for multi-disease recognition	M. Umar et al. (2024)	Achieved 98.8% accuracy in real-time conditions
IoT-based automated aeroponics for environmental monitoring and resource efficiency	N. Sadek et al. (2024)	Productivity doubled, water savings of 80%
EfficientNet combined with group-wise transformers for crop disease detection	J. Feng et al. (2024)	Over 99% accuracy across datasets
YOLOv8 with Grad-CAM++ for real-time monitoring and explainable AI	L. D. Quach et al. (2024)	High classification accuracy of 96.69%, explainable AI
Life Cycle Assessment (LCA) for environmental impact analysis	X. Schmidt Rivera et al. (2020)	Significant GHG reduction, high energy cost

The application of diverse techniques across machine learning, IoT, and image processing to address challenges in agriculture. ISC-MRCNN and APS-DCCNN were employed by Yang et al. for plant leaf segmentation and classification, achieving notable improvements in detection and classification precision. Agarwal et al. utilized a CNN-based model for tomato leaf disease detection, achieving an accuracy of 91.2%, while Zhou et al. proposed the Restructured Deep Residual Dense Network (RRDN), which achieved a higher accuracy of 95%. Lightweight architectures like MobileNetV2 by Ahmed et al. provided efficient computation with an accuracy of 99.3%, showcasing the potential of resource-constrained applications.

In IoT-based solutions, Farooq et al. demonstrated the use of MQTT and HTTP protocols for greenhouse monitoring, which improved crop yield and optimized resource usage. Priya et al. integrated IoT with machine learning in hydroponic systems, achieving 95% validation accuracy. IoT applications also extended to aeroponic systems, where Sadek et al. automated nutrient delivery, doubling productivity and achieving 80% water savings. Similarly, Sharma et al. combined mechanistic and neural models to achieve 90% water efficiency and 80% land savings in controlled environments.

Advanced deep learning techniques such as YOLOv7 and YOLOv8 were used for real-time disease detection and monitoring by Umar et al. and Quach et al., achieving 98.8% and 96.69% accuracy, respectively. Additionally, Feng et al. integrated EfficientNet with group-wise transformers for disease detection, delivering over 99% accuracy across datasets. These methodologies underline the critical role of automation, computational efficiency, and precision technologies in transforming agricultural practices and addressing sustainability challenges.

V. CONCLUSION

The reviewed studies highlight significant advancements in the integration of machine learning, IoT, and image processing technologies for addressing critical challenges in agriculture, including nutrient management, disease detection, and sustainability. Techniques such as ISC-MRCNN for segmentation, PCA-based feature extraction, and lightweight models like MobileNetV2 demonstrated high accuracy and efficiency, making them suitable for diverse applications in precision agriculture. IoT-enabled systems have proven instrumental in optimizing greenhouse and aeroponic farming, with MQTT and HTTP protocols enhancing real-time monitoring and automation, as seen in the works of Farooq et al. and Priya et al. Similarly, advanced deep learning frameworks like YOLOv7 and YOLOv8 have shown exceptional performance in real-time disease detection and crop health monitoring, providing a foundation for scalable solutions.

The methodologies proposed in papers [8] and [13] have been pivotal in guiding the development of the Aeroponic project. Priya et al.'s integration of IoT and machine learning in hydroponic systems served as a model for combining sensor data with automated nutrient delivery. Similarly, the multi-disease detection capabilities demonstrated by Umar et al. using YOLOv7 informed the design of the disease detection framework , enabling real-time monitoring and decision-making. Together, these approaches have enabled the creation of a fully automated aeroponic system that optimizes nutrient delivery and health monitoring while ensuring scalability and resource efficiency.

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