Detection and prediction of diseases in hydroponic farming for sustainable agriculture

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Abstract

Nutrients are crucial for plant growth and health. Inadequate macronutrients can lead to various damage to plants. However, deficiencies of different macronutrients often show similar visual symptoms, creating challenges for farmers to accurately identify them. Leveraging the synergy between computer vision technology and IoT presents a non-destructive approach to monitor and control nutrient levels, particularly in hydroponic systems. Although computer vision helps analyze plant image data based on different characteristics, a single characteristic may not accurately represent overall plant health. Moreover, accurate knowledge of macronutrient deficiency percentages is essential to support advanced precision agriculture systems. In this study, we propose a multi-layer perceptron (MLP) architecture capable of multitasking, including both recognition and estimation tasks. Furthermore, we aim to determine the optimal architecture by considering a combination of three key features: texture, color and leaf shape. Through rigorous analysis and design, our proposed model shows promising potential for simultaneous identification and estimation of macronutrient deficiencies. This model can contribute significantly in advancing precision agriculture practices in India.

I. Introduction

Plants of various types hold significant economic value within the agricultural sector of India. However, production often struggles to meet consumption demands, leading to inflation rates ranging from 0.20% to 0.55% in 2019 [1]. Contributing factors include dwindling land availability due to urbanization, crop failures due to erratic weather patterns, pest infestations, and diseases [2]. To mitigate these challenges, innovative farming methods like hydroponics offer promise, especially in areas with limited land and unpredictable weather conditions [3]. Hydroponic farming focuses on delivering essential nutrients to plants [4]. Both macro and micronutrients are crucial for plant growth and development [5]. Macronutrients such as Nitrogen (N), Phosphorus (P), Potassium (K), Calcium (Ca), Magnesium (Mg), and Sulfur (S) are required in relatively large quantities (> 1000 mg/kg dry matter), while micronutrients including Iron (Fe), Manganese (Mn), Zinc (Zn), Copper (Cu), Chlorine (Cl), Boron (B), and Molybdenum (Mo) are needed in smaller amounts (<100 mg/kg dry matter) [6]. Imbalances in nutrient content can lead to visible symptoms on plant leaves, including chlorosis, leaf distortion, and necrosis [7], [8]. However, distinguishing between different nutrient deficiencies can be challenging due to overlapping visual symptoms [10].In the context of advancing agriculture in India, technological integration plays a crucial role [11]. Monitoring and control systems, integrated with the Internet of Things (IoT), offer solutions for intelligent farming, including automated hydroponic setups [12]. Computer Vision emerges as a key technology for monitoring plant health [13], [14]. By

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combining IoT and computer vision technologies, automated hydroponic systems can assess plant conditions and provide timely solutions Several studies have attempted to estimate the percentage of nutrient deficiencies using plant images [16], [23]. Color characteristics have been utilized in various crops, employing techniques such as Multivariate Linear Regression, Genetic Algorithm, Back Propagation-ANN, and KNN [23], [24]. Texture features have also been explored using algorithms like Support Vector Machine (SVM) [25]. Deep learning approaches, including Recurrent Convolution Neural Network (RCNN), have been applied across different plant types [1]. However, most studies have relied on a single feature for estimation, rendering resulting models less robust across all nutrient types [26], as each nutrient exhibits distinct visual characteristics. In India, where agricultural challenges are diverse and complex, there is a pressing need for comprehensive solutions. This study aims to address this need by proposing a novel approach that integrates multiple features for simultaneous identification and estimation of nutrient deficiencies across various plant types, thereby enhancing the precision and effectiveness of agricultural practices.

Computer vision relies on image data for analysis, with various color models being employed, including the RGB model [15], [16]. Several studies have explored the identification of nutrient deficiencies in plants using leaf images, employing algorithms such as K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), Naïve Bayes, Multi-Layer Perceptron (MLP), and Convolutional Neural Network (CNN) with diverse architectures [17], [18], [19]. While MLP has shown promise, most studies have focused solely on identifying nutrient deficiency types [20]. Achieving precise agricultural practices requires estimating the percentage of nutrient deficiencies to tailor nutrient solutions to plant requirements [21], [22].

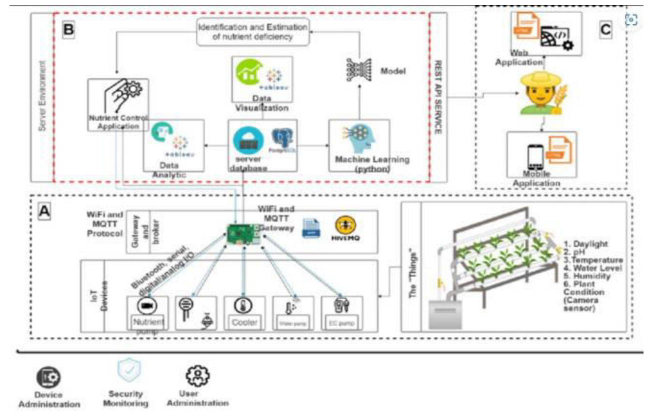

Fig.1.Introduction to Working System

II. Literature review

The literature review you've provided offers a comprehensive overview of existing research efforts in the field of nutrient deficiency identification and estimation in plants using computer vision technologies. Let's delve deeper into some key points:

A. Nutrient Deficiency Identification:

Methodologies: The review mentions various machine learning algorithms employed for nutrient deficiency identification, ranging from traditional classifiers like KNN, Naïve Bayes, and MLP to more advanced techniques like CNNs. It would be beneficial to discuss the strengths and weaknesses of each approach, as well as any comparative studies that have evaluated their performance in this specific context. Data Acquisition and Preprocessing: Further detail could be provided on how leaf images are captured and processed before being fed into the machine learning models. This might include considerations such as image resolution, lighting conditions, and preprocessing techniques like normalization or augmentation.

B. Challenges in Classification:

Expanding on the challenges of distinguishing between similar nutrient deficiencies could involve discussing specific examples where certain deficiencies may exhibit overlapping symptoms. Additionally, exploring how these challenges might vary across different plant species or environmental conditions could provide valuable insights.

C. Nutrient Deficiency Estimation:

Feature Extraction Techniques: In addition to color and texture features, the review briefly mentions the use of leaf shape as a potential feature for nutrient deficiency estimation. Elaborating on how these features are extracted from images and their relevance to estimating deficiency percentages could offer a more comprehensive understanding.

D. Model Evaluation:

Discussing the metrics used to evaluate the performance of deficiency estimation models, such as mean squared error or coefficient of determination, would provide clarity on how researchers assess the accuracy of their predictions.

E. Integration of Multiple Features:

While the review acknowledges the limitation of relying on a single feature for estimation, exploring strategies for integrating multiple features into a unified model could be beneficial. This could include techniques like feature fusion, where information from different modalities (e.g., color, texture, shape) is combined to improve predictive performance.

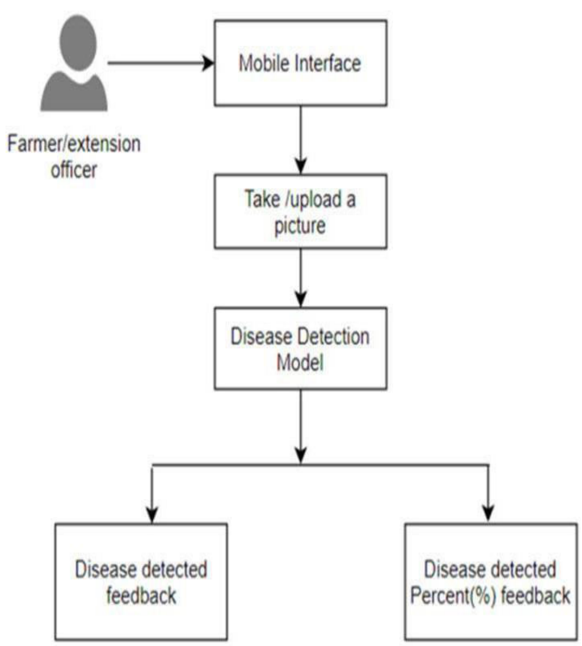

Fig.2. Use Case Diagram

A. Challenges and Opportunities:

Generalization Across Plant Types: Delving into the specific challenges associated with generalizing nutrient deficiency identification and estimation models across different plant species or cultivars could shed light on the complexities of this task. Factors such as leaf morphology, growth habits, and nutrient uptake mechanisms may influence the transferability of models between plant types.

B. Data Annotation and Labeling:

Discussing the process of annotating leaf images with ground truth labels for nutrient deficiencies could highlight potential sources of bias or variability in the training data, as well as strategies for mitigating these issues.

C. Real-time Implementation:

Exploring the feasibility of deploying computer vision-based nutrient monitoring systems in real-world agricultural settings, including considerations of computational resources, scalability, and cost-effectiveness, would be relevant for assessing the practical utility of these technologies.

D. Interdisciplinary Collaboration:

Emphasizing the importance of interdisciplinary collaboration between researchers, agricultural practitioners, and technology experts is crucial for identifying research priorities and translating scientific advancements into practical solutions. Discussing specific examples of successful collaborations or potential avenues for partnership could provide concrete recommendations for future endeavors.

E. Ethical and Societal Implications:

Considering the broader ethical and societal implications of deploying automated nutrient monitoring systems in agriculture, such as issues related to data privacy, equity, and environmental sustainability, could enrich the discussion and inform future research agendas. By exploring these additional dimensions, researchers can gain a more nuanced understanding of the challenges and opportunities in leveraging computer vision technologies for nutrient deficiency identification and estimation in agriculture, ultimately guiding the development of more effective and sustainable solutions.

F. Classification of Crop Diseases:

Infectious Diseases: These are caused by pathogens such as fungi, bacteria, and viruses. They often spread rapidly under favorable environmental conditions, leading to widespread crop damage. Fungal diseases, such as black leaf mould and powdery mildew, thrive in warm and humid conditions, affecting various parts of the plant including leaves, stems, and fruits. Bacterial diseases, like bacterial spots, can cause lesions on leaves and fruits, leading to reduced yield and quality. Viral diseases, though less common, can have severe consequences on crop health and productivity, affecting processes like photosynthesis and nutrient uptake.

G. Non-Infectious Diseases:

These are caused by environmental factors and deficiencies in essential nutrients, leading to physiological disorders in plants. Nutrient deficiencies, such as nitrogen, phosphorus, and potassium deficiencies, can result in stunted growth, leaf discoloration, and reduced yield. Soil acidity and mineral toxicities can disrupt nutrient uptake and physiological processes in plants, affecting their overall health and productivity. Machine learning techniques, particularly deep learning algorithms, offer significant advantages in disease detection by analyzing large volumes of image data to identify patterns and anomalies. The choice of tomato plants for this project is strategic due to their economic importance, widespread cultivation, and susceptibility to various diseases. Hydroponic cultivation of tomatoes presents unique challenges and opportunities, including controlled environments that can influence disease development and crop quality.

Target Diseases:

The selection of specific diseases for focus allows for a more targeted approach in disease management and mitigation strategies. Each targeted disease presents distinct symptoms and challenges in detection, requiring tailored algorithms and image processing techniques for accurate identification.

H. Existing ML-based Image Processing:

The integration of RGB cameras and single-board computers like Nvidia Jetson TX1 demonstrates the practical application of machine learning in real-world agricultural scenarios. Deep learning models, such as AlexNet and SqueezeNet, offer high accuracy in disease detection by leveraging large-scale image datasets for training and validation.

I. Image Segmentation and Classification Techniques:

Image segmentation techniques, such as k-means clustering and HSV color spacing, play a crucial role in isolating diseased regions within plant images for further analysis. Classification methods like CNNs, SVMs, and GWT offer diverse approaches to categorizing and labeling image data, with CNNs being particularly effective for tasks involving spatial dependencies and feature extraction.

J. Method Selection:

The selection of appropriate image processing and machine learning methods depends on factors such as image quality, computational resources, and the specific characteristics of the target crop and disease.

The adoption of CNNs for image classification reflects their versatility and performance in handling complex visual data, making them well-suited for tasks like disease detection in agriculture.

III. CNN Model Architecture:

The architecture of CNNs is characterized by hierarchical layers that progressively extract and transform features from raw input data. Each layer in a CNN performs specific operations, such as convolution, pooling, and normalization, contributing to the model's ability to learn hierarchical representations of input images. By addressing these aspects comprehensively, the project aims to advance the field of agricultural technology by providing scalable and efficient solutions for disease detection and management in crops, ultimately contributing to global food security and sustainability.

In today's interconnected world, the demand for intelligent and efficient computing systems is ever- growing, especially in domains requiring real-time processing and low power consumption. Embedded systems, with their dedicated functions within larger mechanical or electrical systems, play a pivotal role in fulfilling these requirements. Image processing, a fundamental aspect of many embedded applications, finds crucial applications in diverse fields such as IoT devices, drones, wearable devices, and agricultural monitoring systems.

Embedded systems are characterized by limited processing power and memory, making efficient resource utilization imperative. This limitation necessitates the use of optimized algorithms and lightweight frameworks for image processing tasks. On the other end of the spectrum, personal computers (PCs) offer ample computing resources, making them suitable for intensive image processing tasks. Additionally, cloud computing platforms provide scalability and flexibility, allowing users to deploy and scale image processing applications as needed, particularly beneficial for applications with large datasets or complex processing requirements. MATLAB, a popular platform for numerical computing, stands out as a go-to tool for image processing and machine learning tasks. With its comprehensive set of tools and functions tailored for image processing, MATLAB enables researchers and practitioners to perform a wide range of tasks, including feature extraction, segmentation, and classification, with ease and efficiency. Single-board computers (SBCs) such as Raspberry Pi and Nvidia Jetson TX1 offer a balance between computational power and cost-effectiveness, making them ideal for embedded image processing applications. Equipped with interfaces for connecting camera modules, these SBCs enable on-device processing, making them suitable for real-time applications like agricultural monitoring.

In recent years, the emergence of TinyML has revolutionized machine learning deployment on constrained edge devices. TensorFlow Lite for Microcontrollers (TF Lite Micro) is a prime example, offering a framework specifically optimized for running machine learning models on devices with limited resources. This enables real-time ML tasks on low-powered devices, opening up new possibilities for embedded applications.

Machine learning on mobile devices further extends the reach of intelligent computing. Frameworks like TensorFlow Lite and PyTorch provide seamless integration and efficient execution of ML models on smartphones and tablets. Apache Spark and Shogun offer distributed computing and versatile machine learning capabilities, catering to diverse application requirements.

In the context of the project discussed, utilizing TensorFlow for building the CNN model offers several advantages. TensorFlow Lite enables deployment of the ML model on multiple edge devices, ensuring broader accessibility and deployment options. Compatibility with mobile platforms ensures seamless integration and efficient execution on devices with varying computational resources. Furthermore, TensorFlow's extensive ecosystem and community support provide resources and tools for model development, optimization, and deployment across different platforms.

In conclusion, the convergence of image processing and machine learning technologies with embedded systems holds immense potential for driving innovation across various domains. As technology continues to advance, the integration of intelligent computing capabilities into embedded systems will undoubtedly pave the way for groundbreaking applications and solutions.

IV. Proposed method

A. Sensor Deployment:

Choose sensors that are reliable, accurate, and suitable for the specific requirements of hydroponic farming. Ensure proper placement of sensors throughout the hydroponic system to capture representative data from different parts of the farm. Use wireless or IoT-enabled sensors for seamless data collection and integration into the monitoring system.

B. Data Collection:

Implement robust data logging mechanisms to ensure continuous and reliable data collection. Consider using cloud-based storage solutions for scalability and accessibility of the collected data. Regularly calibrate sensors to maintain data accuracy and consistency.

C. Data Preprocessing:

Explore various techniques for data cleaning, such as outlier detection, smoothing, and interpolation. Normalize or standardize sensor readings to facilitate comparison and analysis across different parameters. Handle missing data appropriately through imputation or exclusion strategies.

D. Feature Extraction:

Engage domain experts to identify relevant features that can provide insights into plant health and disease status. Consider using advanced techniques such as signal processing, image analysis, and spectral analysis for feature extraction from sensor data and imagery. Employ dimensionality reduction techniques if dealing with high-dimensional data to improve computational efficiency and model performance.

E. Machine Learning Models:

Experiment with different machine learning algorithms such as decision trees, random forests, support vector machines, and neural networks to find the most effective models for disease detection. Fine-tune hyperparameters and conduct cross-validation to optimize model performance and generalization.
Evaluate models using appropriate metrics such as accuracy, precision, recall, and F1-score.

F. Anomaly Detection:

Choose anomaly detection algorithms based on the nature of the data and the types of anomalies expected in the hydroponic system.Set appropriate thresholds or utilize unsupervised learning techniques to detect anomalies without labeled data. Incorporate feedback mechanisms to adjust detection thresholds dynamically based on changing environmental conditions.

G. Predictive Analytics:

Explore time series forecasting methods such as autoregressive models, moving averages, and ARIMA (AutoRegressive Integrated Moving Average) models for predicting disease outbreaks.

Consider integrating external factors such as weather forecasts, pest infestation patterns, and crop growth stages into predictive models for improved accuracy. Validate predictive models using historical data and assess their performance using metrics such as mean absolute error and root mean squared error.

H. Integration with Decision Support Systems:

Develop user-friendly interfaces and dashboards that visualize real-time data, disease alerts, and recommendations for farmers. Implement notification mechanisms such as email alerts or mobile notifications to ensure timely responses to detected anomalies or predicted disease outbreaks.

Enable remote monitoring and control capabilities to facilitate proactive management of the hydroponic farm.

I. Continuous Monitoring and Feedback Loop:

Establish procedures for ongoing monitoring and evaluation of the detection and prediction system's performance. Solicit feedback from end-users, such as farmers and agricultural advisors, to identify areas for improvement and prioritize enhancements. Regularly update models and algorithms based on new data, emerging trends, and evolving disease patterns to maintain relevance and effectiveness.

J. Collaboration with Agricultural Experts:

Foster collaboration between data scientists, engineers, and agricultural experts to leverage complementary skills and domain knowledge. Organize workshops, seminars, or collaborative projects to facilitate knowledge sharing and interdisciplinary research in hydroponic farming and disease management. Encourage open communication and feedback exchanges to ensure that the developed solutions align with the practical needs and challenges faced by hydroponic farmers. By incorporating these additional details and considerations into the proposed method, hydroponic farmers can enhance the effectiveness and sustainability of disease detection and prediction efforts in their farming practices.

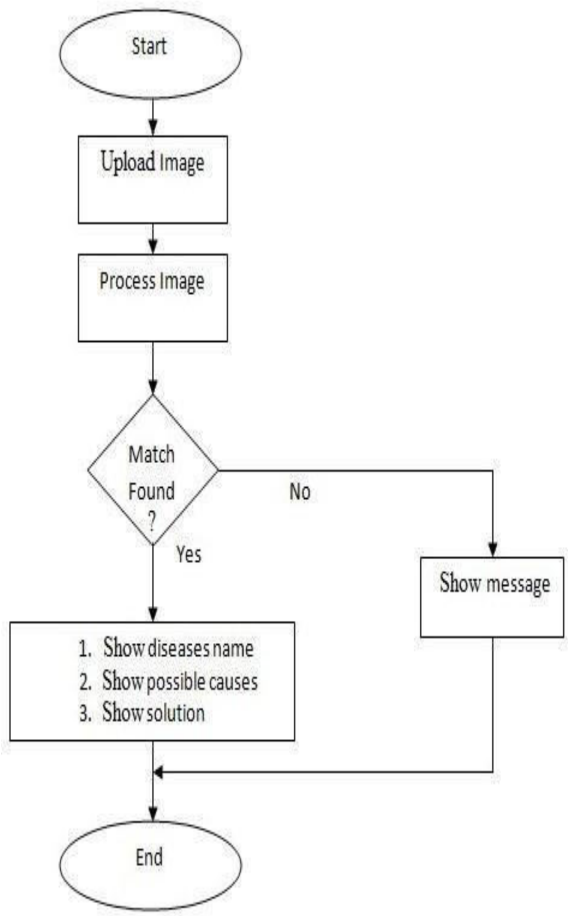

Fig.3. Flow chart for the proposed system

V. Result Analysis

The excerpt provided outlines the process of training and testing a Convolutional Neural Network (CNN) model for the classification of images related to diseases in hydroponic farming. In this response, I'll expand upon the key concepts and processes described in the excerpt, providing a detailed explanation of each step involved in training the CNN model, evaluating its performance on validation and test sets, and deploying it on an iOS device. Additionally, I'll discuss the implications of transforming the model into the TensorFlow Lite (TFLite) format.

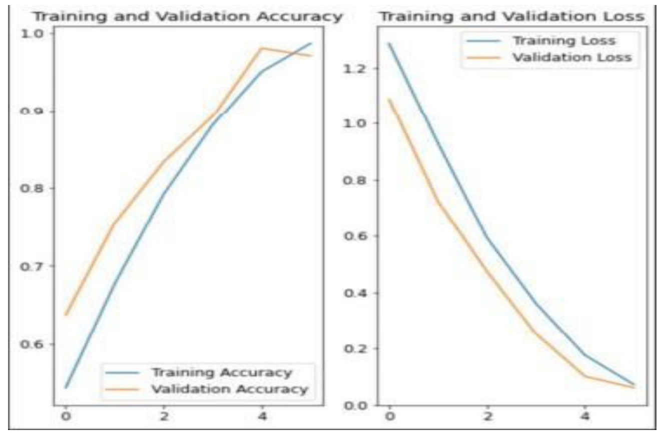

Fig.4. Visualisation of training and validation accuracies and losses

Introduction to CNNs in Image Classification:

Provide an overview of CNNs and their role in image classification tasks. Explain the architecture of CNNs, including convolutional layers, pooling layers, and fully connected layers. Discuss the importance of CNNs in various fields, including agriculture, for tasks such as disease detection in plants.

A. Data Preprocessing and Augmentation:

Describe the preprocessing steps applied to the image data, such as resizing, normalization, and data augmentation. Explain the purpose of data augmentation in increasing the diversity and robustness of the training dataset. Discuss techniques used for data augmentation, such as rotation, flipping, and adjusting brightness.

B. Model Training and Validation:

Detail the process of training the CNN model using the training dataset. Explain the choice of loss function (Sparse Categorical Crossentropy) for computing the loss between predicted and true labels. Discuss the use of the validation set for monitoring model performance during training and preventing over fitting. Analyze the behavior of the model's accuracy and loss over multiple epochs, highlighting the correlation between decreasing loss and increasing accuracy.

C. Evaluation on Test Set:

Describe the process of evaluating the trained model on the test set. Discuss the characteristics of the test set, including its composition and the challenges posed by variations in brightness and image orientation.

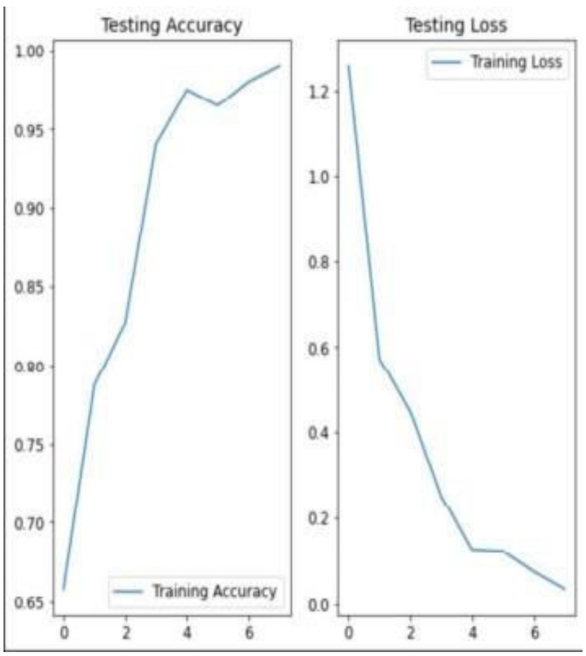

Fig.5.Visualization of testing accuracy and loss

Present the results of the model's accuracy and loss on the test set after multiple epochs of testing. Performance on iOS Device: Explain the process of deploying the trained CNN model on an iOS device. Discuss any challenges or considerations specific to deploying machine learning models on mobile devices. Present the accuracy achieved by the model on the iOS device for classifying images of tomato leaves with Black mould disease. Implications of Model Transformation to TFLite Format:

Discuss the process of converting the trained CNN model into the TensorFlow Lite (TFLite) format.

Explain the potential impact of model transformation on accuracy and performance. Consider factors such as model size, computational efficiency, and compatibility with mobile devices. Conclusion and Future Directions: Summarize the findings of the study, including the performance of the CNN model on training, validation, and test sets. Discuss potential future directions for improving the model's accuracy and scalability, such as fine-tuning hyperparameters, incorporating additional data sources, or exploring advanced CNN architectures.

By elaborating on each aspect of the training, testing, and deployment process outlined in the excerpt, this response will provide a comprehensive explanation of the CNN model's development and performance evaluation for disease classification in hydroponic farming. Comparison with other Systems:

In the pursuit of sustainable agriculture, hydroponic farming has emerged as a promising solution for efficient crop production. However, like traditional farming methods, hydroponic systems are susceptible to plant diseases, which can significantly impact crop yield and quality. To address this challenge, various systems for disease detection and prediction have been developed, each with its unique strengths and limitations. In this essay, we will conduct a comparative analysis of these systems, with a focus on their applicability, performance, and implications for sustainable agriculture.

D. Traditional Manual Inspection:

Traditionally, farmers have relied on manual inspection to detect diseases in hydroponic crops. While this approach is straightforward and familiar to farmers, it has several limitations. Manual inspection is labor-intensive and time-consuming, often resulting in delays in disease detection. Moreover, the subjective nature of human observation can lead to inconsistencies in disease diagnosis and treatment decisions.

E. Rule-Based Systems:

Rule-based systems utilize predefined rules or heuristics to detect diseases based on observed symptoms or environmental conditions. While these systems are relatively simple to implement and understand, they lack the flexibility and adaptability required to handle complex disease patterns and dynamic environmental factors. Additionally, rule-based systems may struggle to maintain accuracy in the face of evolving disease strains or environmental changes.

F. Non-AI Machine Vision Systems:

Non-AI machine vision systems automate image analysis processes to detect diseases based on visual cues captured by cameras or sensors. These systems offer the advantage of objective and consistent assessments of plant health. However, they often require extensive manual feature engineering and may struggle to handle variations in plant appearance and environmental conditions effectively. AI-Based Systems (e.g., CNNs) Artificial intelligence (AI)-based systems, particularly Convolutional Neural Networks (CNNs), have gained traction for disease detection in hydroponic farming. CNNs can learn complex patterns and features directly from data, enabling them to adapt to diverse disease types and environmental conditions. While AI-based systems require large amounts of labeled data for training and are computationally intensive, they offer unparalleled accuracy and scalability in disease detection.

G. Integrated IoT Solutions:

Integrated IoT solutions combine sensor data with AI algorithms for real-time monitoring and decision- making in hydroponic farming. These solutions offer holistic insights into environmental conditions and plant health, facilitating timely interventions to prevent disease outbreaks. However, they require significant upfront investment in hardware and infrastructure, and integration and maintenance can be complex.

H. Commercial Hydroponic Monitoring Systems:

Commercial hydroponic monitoring systems provide comprehensive solutions with hardware, software, and support services for disease detection and monitoring. While these systems offer user-friendly interfaces and actionable insights, they are often proprietary and expensive, limiting their accessibility to small-scale farmers.

I. Research Prototypes and Academic Models:

Research prototypes and academic models push the boundaries of technology with innovative algorithms and approaches for disease detection in hydroponic farming. While these models are often open-source and accessible for experimentation, they may lack robustness, scalability, or real-world validation, necessitating adaptation and optimization for practical deployment disease detection systems in hydroponic farming encompass a range of approaches, each with its advantages and challenges. While traditional manual inspection methods remain prevalent, AI-based systems, particularly CNNs, hold promise for achieving high accuracy and scalability in disease detection. However, challenges such as data requirements, computational resources, and model interpretability need to be addressed to realize the full potential of AI-based systems in hydroponic agriculture. Ultimately, a combination of AI techniques with other monitoring systems or expert knowledge may offer the most effective solution for sustainable disease management in hydroponic farming.

Conclusion:

In the world of permaculture, hydroponic farming stands out as a new method with many benefits such as efficiency and reduced environmental impact. But like all farming methods, hydroponic farming has its challenges, including the threat of plant diseases. Timely and accurate detection of diseases is important to prevent crop loss and ensure the stability of hydroponic systems. Against this background, the development of advanced technologies, especially deep learning models such as convolutional neural networks (CNN), holds great promise.

The project discussed in this article aims to solve the challenge of disease detection in hydroponic farming using CNN-based models. Classification as a model. The model is designed to detect disease when a leaf is present and provide a good way to control the disease. The main goal throughout the project is to increase efficiency and effectiveness, especially in the global hydroponic farming environment. The results obtained during training and validation show the effectiveness of the CNN model. The model demonstrated the ability to identify images indicating leaf diseases, achieving 98.98% accuracy during the training period and 100% accuracy during the validation period. Moreover, the performance continues to be tested with 99.01% accuracy and low loss rate. These results demonstrate the potential for practical use of this model in hydroponic farming.

However, it is important to know the limitations and areas for improvement encountered during the study. Although the model showed high accuracy in tests, its performance on images of the real hydroponic farm has not been tested. This difference indicates the need to further refine and improve the model in the real world to ensure that its results are good in different situations. Looking forward, future work in this area should focus on several key areas to improve the utility of CNN-based disease diagnosis. It is important to integrate image processing subsystems into hydroponic systems to enable instant monitoring and automatic decision making.

The results of image processing can be combined with other data collected from the hydroponic farm, such as environmental parameters and nutrient levels, to create a dashboard that provides a better understanding of farmers. Additionally, expanding the disease classification to include more plant diseases will strengthen the use and effectiveness of these systems. This expansion could allow for better disease control by reducing the need for farmers to monitor. Additionally, the use of built-in training for mobile devices provides the opportunity to improve the performance of the model over time, making it possible to adapt to changes in the model range, disease, and environment.

In summary, this project represents the development of disease detection in hydroponics using CNN-based classification models. Although initial results are encouraging, further research and development is needed to verify the model's performance in real conditions and integrate it into hydroponic farming systems. Through the use of technology and integration, the goals of hydroponic permaculture can be achieved, ensuring food security and environmental sustainability for future generations

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