J. Electrical Systems 20-9 s (2024): 1967-1973

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IoT-Based Framework for Implementation of Leaf Color Chart for Nitrogen Monitoring in Crop

Abstract: - Effective nitrogen management is essential in precision agriculture to optimize crop yields and promote environmental sustainability. Conventional techniques for evaluating nitrogen levels, although commonly used, suffer from a lack of accuracy and scalability. This research presents a novel design framework that combines the Leaf Colour Chart (LCC), a well-established agricultural tool for nitrogen evaluation, with modern Internet of Things (IoT) technologies. The proposed system utilizes specialized sensors to gather precise leaf color data, which is subsequently analyzed using cloud-based computer vision techniques to correctly and instantaneously predict nitrogen levels. The framework streamlines data gathering and processing, allowing for accurate nitrogen management. This enables the application of fertilizer to specific areas and minimizes wastage. This article provides an overview of the system architecture, examines the difficulties and resolutions in integrating Internet of Things (IoT) technology in agriculture, and showcases case studies that demonstrate the effectiveness of the framework in practical environments. The incorporation of IoT technology with the Leaf Colour Chart signifies a notable progression in agricultural technology, offering the potential to enhance crop management techniques and support sustainable agriculture endeavors.

Keywords: Machine learning, Leaf color chart, precision farming, internet-of-things

INTRODUCTION

The Smart farming refers to the application of the Internet of Things (IoT) in the agricultural sector. This technology provides farms with a variety of sensors, cameras, and other monitoring equipment that gather and send data to centralized or cloud-based systems for immediate analysis[1]. The Internet of Things (IoT) improves farmers' capacity to monitor essential factors including soil moisture, climate conditions, and crop health with unparalleled accuracy. The advantages of incorporating IoT into agricultural practices are numerous, encompassing improved accuracy in the allocation of resources, more effective control over farm inputs such as water and fertilizers, and the mechanization of farming operations, all of which result in heightened efficiency and diminished environmental footprint[2][3]. Managing nitrogen levels in crops is essential in this context since it plays a critical role in promoting plant development and maintaining plant health. Nitrogen plays a crucial role in the production of proteins and chlorophyll in plants, however, effectively managing nitrogen levels may be challenging and demands accuracy. Excessive use of nutrients can result in the runoff of these substances, which can lead to pollution of water and deterioration of soil. On the other hand, insufficient use of nutrients can negatively impact the health and productivity of crops. Efficient nitrogen management is crucial for maximizing crop growth, increasing production, and reducing negative environmental impacts.

The objective of this research is to provide a design framework that utilizes the Leaf Colour Chart (LCC), a method employed for evaluating the nitrogen levels in plants, inside an Internet of Things (IoT) context. This system aims to use advanced IoT technology to integrate LCC and give accurate, real-time evaluations of nitrogen levels in crops. This would enable tailored treatments to be implemented. We describe the conceptualization and implementation of a system that utilizes sophisticated sensors and data analytics to enhance nitrogen management methods. Furthermore, the presentation will present empirical evidence derived from case studies and pilot deployments to substantiate the efficacy of this IoT-enhanced method. This research enhances the progress of precision agriculture by examining how IoT technologies and conventional farming methods intersect. The objective is to showcase how the implementation of intelligent farming techniques can result in more environmentally friendly agricultural operations through improved resource allocation and less ecological impact.

LITERATURE REVIEW

A. *Nitrogen in Crop Management*

Nitrogen is essential for plant growth as it plays a crucial role in the production of proteins and chlorophyll. Efficient management is crucial for maximising plant health and productivity. Conventional techniques for evaluating nitrogen levels are soil nitrate testing[7], plant tissue testing[8][9][10], and the utilisation of chlorophyll meters[11][12][13]. Each of these methods possesses distinct applications as well as limitations. Soil testing methods like the Kjeldahl method and Dumas method can reliably quantify the total nitrogen content in soil. However, they may not precisely indicate the amount of nitrogen that is available to plants

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during the entire growing season. Plant tissue testing provides direct information on the plant's nutritional condition, however it is not practical for making immediate management decisions.
Chlorophyll metres, which use chlorophyll content to assess nitrogen levels, offer prompt results but necessitate calibration and may be too expensive for extensive application. Recent progress has been made in the field of spectrum analysis techniques [16][17][18] and remote sensing technologies [19][20].
These techniques utilise reflectance data to evaluate the health of plants and are becoming more commonly employed for extensive, non-invasive monitoring of crop nitrogen levels.
The adoption of technologies such as the Normalized Difference Vegetation Index (NDVI) and Red Edge NDVI in precision agriculture is renowned for their ability to estimate biomass and nitrogen content from aerial photos

B. Leaf Color Chart (LCC)

The Leaf Color Chart (LCC) offers a straightforward, low-tech approach to nitrogen management. It is a visual tool that matches the color of crop leaves against a graded series of green hues, each corresponding to different nitrogen levels. Studies by organizations like the International Rice Research Institute (IRRI) have proven the effectiveness of LCC in optimizing nitrogen use, especially in rice cultivation [23][24]. The LCC helps in reducing nitrogen waste by enabling farmers to apply fertilizers more carefully based on actual crop needs. The simplicity and cost-effectiveness of the LCC make it particularly valuable in resource-limited settings. Research in regions such as South Asia, as documented in agricultural journals, shows that LCC usage can lead to significant reductions in nitrogen fertilizer usage while maintaining or increasing crop yields [25][26]. This approach not only lowers the cost for farmers but also mitigates environmental risks like nitrate leaching and eutrophication.

Table 1: Leaf Color Chart for Nitrogen Management in Crops

Color Index	***Color Representation***	***Nitrogen Level***	***Significance***	***Recommended Action***
1	Light Green	Low	Nitrogen deficiency	Increase nitrogen application
2	Medium Light Green	Slightly Low	Mild deficiency	Slightly increase nitrogen application
3	Medium Green	Adequate	Optimal for growth	Maintain current nitrogen application
4	Dark Green	High	Excess nitrogen	Reduce nitrogen application
5	Very Dark Green	Very High	Potential toxicity	Significantly reduce nitrogen application

The provided Table 1 serves as a practical tool for interpreting the Leaf Color Chart, utilized to assess nitrogen levels in crop leaves. Each shade of green, ranging from light to very dark, corresponds to varying levels of nitrogen content, from low to very high. Light green indicates a significant nitrogen deficiency, suggesting the need for additional fertilizer to support healthy growth. The recommended action is to increase nitrogen application to correct the deficiency. Medium light green indicates a slight nitrogen deficiency, suggesting a mild increase in nitrogen could benefit growth without over-fertilizing. Medium green signifies an adequate nitrogen level, optimal for crop growth. Maintaining the same nitrogen application level is advised. Dark green indicates high nitrogen content, potentially beyond the crop's optimal use, risking environmental harm. The advisable action is to reduce nitrogen application to prevent wastage. Very dark green signals an extremely high nitrogen level, potentially toxic to the plant. Significant reduction or halting of nitrogen application is recommended to mitigate toxicity. By aligning fertilization strategies with the chart insights, farmers can optimize plant health, and yield, and reduce environmental impact

C. IoT in Precision Agriculture

IoT technologies have brought a new dimension to precision agriculture through real-time data collection and analysis. These technologies include soil moisture sensors [27], atmospheric sensors [28], GPS-guided equipment[29], and IoT-enabled drones[30][31] equipped with advanced imaging for detailed crop monitoring. For instance, soil sensors like the Tensiometers and Capacitance sensors measure soil moisture levels to optimize irrigation schedules [32]. Drones equipped with multispectral sensors can perform detailed assessments of crop health, identifying issues such as nutrient deficiencies and pest infestations [33]. Further integrating IoT, automated agricultural machinery like self-driving tractors and robotic harvesters utilize GPS and IoT for precise operation, significantly reducing the need for manual labor [34]. Environmental monitoring stations utilizing IoT technologies provide farmers with continuous data on climate conditions, enabling them to adapt their farming practices to changing environmental variables effectively. By combining these advanced IoT applications with traditional tools like the LCC, it is possible to enhance the precision and efficiency of nitrogen management. For example, integrating IoT color sensors with LCC techniques could automate the monitoring process, providing continuous, real-time nitrogen status data, which can be directly utilized to adjust fertilizer application rates dynamically. This not only ensures optimal nitrogen usage but also aligns agricultural practices with sustainable farming objectives, reducing environmental impacts and enhancing crop productivity.

IOT-BASED DESIGN FRAMEWORK

The proposed IoT-based design framework integrates a comprehensive system architecture designed to optimize nitrogen management in crops using advanced technologies. Fig.1 shows the architecture comprises three main components: data collection sensors, data transmission networks, and user interfaces.

D. Components of Framework

- Sensors: These are strategically placed throughout the crop fields to collect data continuously. Sensors not only monitor the color of crop leaves but also gather environmental data crucial for assessing crop health.
- Data Transmission: Data collected by the sensors is transmitted in real-time through low-power wide-area networks (LPWAN)[35], such as LoRaWAN or NB-IoT[36]. These technologies are chosen for their long-range capabilities and low battery consumption, suitable for rural and expansive agricultural settings.
- Cloud Computing Platform: Once transmitted, data is aggregated and processed in a cloud-based platform that can handle large volumes of data, allowing for complex analyses and data storage.
- User Interfaces: The system provides real-time data and insights via user-friendly dashboards accessible on web and mobile platforms. These interfaces allow for immediate action and interaction by the farm managers and agronomists.

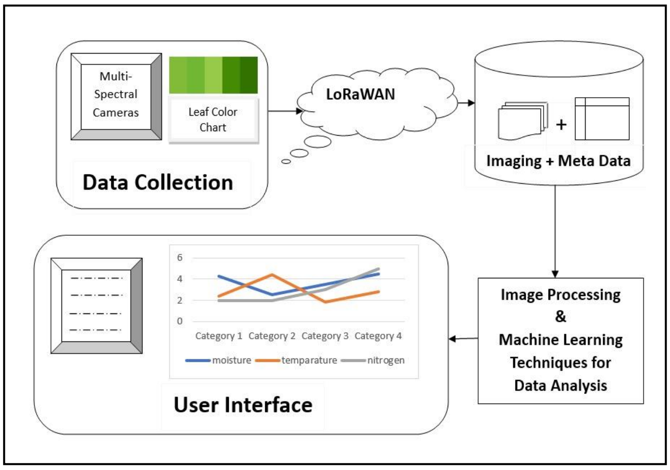

Fig 1. IoT-Based Framework for Leaf Color Chart for Nitrogen Monitoring in Crop

The framework utilizes a diverse array of sensors to ensure comprehensive monitoring and data collection:

- Multispectral Cameras: These capture images in multiple wavelengths of light to detect plant health indicators not visible to the naked eye. They can identify stress before physical symptoms appear by assessing changes in the light reflectance of plant leaves.
- Leaf Color Sensors: These sensors are crucial for a digital version of the leaf color card (LCC), quantifying the greenness of leaves which directly correlates to nitrogen content.
- Environmental Sensors: Such sensors include thermometers, humidity sensors, and CO2 detectors, providing data that influences plant metabolism and nutrient uptake.

In this setup, sensor data acquisition is automated and continuous, with sensors programmed to transmit data at predefined intervals. This consistent monitoring guarantees swift detection and response to changes in both crop health and environmental conditions. The collected data undergoes thorough processing and analysis using cutting-edge techniques

- Image Processing Algorithms: These algorithms analyze data from multispectral cameras, extracting features related to vegetation indices such as NDVI (Normalized Difference Vegetation Index)[37] or GNDVI (Green Normalized Difference Vegetation Index), which are critical indicators of plant health and nitrogen status.
- Machine Learning Models: Leveraging historical and real-time data, machine learning models predict crop nitrogen[38][39] needs and potential stress conditions. Techniques such as supervised learning models are used to predict yield based on nitrogen levels and environmental conditions.
- Data Fusion Techniques: This involves integrating various data streams (sensor data, environmental data, and historical crop performance data) to provide a holistic view of the current crop state. Techniques such as Kalman filters[40] or ensemble methods[41] may be used to enhance prediction accuracy and reliability.

In the last phase of data analysis, the cloud platform enables robust capabilities for extensive analysis, leveraging big data analytics and AI to handle the large volumes of collected data. The cloud infrastructure further enables scalability and real-time processing, crucial for making timely decisions. From data processing to actionable insights, the system ensures practicality and relevance. It generates detailed recommendations for nitrogen application rates and timing, tailored to each crop section based on real-time data

- Automated Fertilizer Systems: Integrated with IoT, these systems can adjust nitrogen application automatically, applying more precise amounts where and when needed, based on the system's recommendations.
- Irrigation Systems: Adjustments to irrigation schedules can be automated to enhance nitrogen uptake, preventing leaching, and ensuring optimal growth conditions.

By leveraging advanced IoT technologies, this framework not only enhances nitrogen management but also contributes to sustainable agriculture practices by reducing waste and increasing crop yield efficiency. The comprehensive use of sensors, data analytics, and automated systems provides a robust solution to the challenges of modern agriculture.

METHODOLOGY

This section presents the methodology for data analysis and the recommender system, comprising four key steps. The initial step involves Image Preprocessing, wherein images undergo normalization and calibration to rectify lighting conditions and camera biases. Subsequently, Color Extraction identifies the dominant color on the leaf and converts it to a standard color space. In the subsequent color matching step, the extracted color is compared against a predefined Leaf Color Chart to estimate nitrogen content. Finally, a decision support system generates actionable insights based on the estimated nitrogen levels. Below is a basic pseudo code outlining this process.

```
Function preprocessImage(image, ambientData):
calibratedImage = calibrateImage(image, ambientData.lightIntensity)
normalizedImage = normalizeImage(calibratedImage)
return normalizedImage
function extractColor(image):
dominantColor = getDominantColor(image)
cielabColor = convertRGBtoCIELAB(dominantColor)
return cielabColor
function matchColorToNitrogen(cielabColor, colorChart):
closestColor = findClosestColorMatch(cielabColor, colorChart)
nitrogenLevel = getNitrogenLevel(closestColor)
return nitrogenLevel
function generateRecommendations(nitrogenLevel, cropData):
recommendation = calculateFertilizerNeed(nitrogenLevel, cropData)
return recommendation
// Main routine
ambientData = getAmbientSensorData()
image = captureLeafImage()
preprocessedImage = preprocessImage(image, ambientData)
leafColor = extractColor(preprocessedImage)
nitrogenEstimate = matchColorToNitrogen(leafColor, LeafColorDatabase)
recommendation = generateRecommendations(nitrogenEstimate, CropSpecificData)
displayRecommendation(recommendation)
```

Pseudocode includes four main functions, to implement them various mathematical formulas are needed. To normalize image colors based on ambient light intensity and a calibration card:

$$Inormalized = \frac{(I - Imin) \times (Tmax - Tmin)}{Imax - Imin} + Tmin \qquad (1)$$

In Equation 1. Where I is the original image intensity, Imin and Imax are the minimum and maximum intensities in the image, Tmin and Tmax are target range values, typically 0 to 255 for each color channel. For Color Space Conversion Convert RGB to CIELAB to facilitate accurate color difference calculation:

$$L^* = 116 \times f(Y/Y_n) - 16 \qquad (2)$$

$$a^* = 500 \times (f(X/X_n) - f(Y/Y_n)) \qquad (3)$$

$$b^* = 200 \times (f(Y/Y_n) - f(Z/Z_n)) \qquad (4)$$

Where in Equation (2). X_n, Equation (3) Y_n and Equation (4) Z_n are reference variables. In color matching Euclidean distance is calculated in CIELAB space to find the closest match on the LCC

$$d = \sqrt{L1 - L2)^2 + (a1 - a2)^2 + (b1 - b2)^2} \qquad (5)$$

Where Equation (5). L1, a1 ,b1 are from the measured leaf and L2,a2,b2 are from the chart values. In fertilizer Recommendations nitrogen level estimation is used to calculate fertilizer needs based on crop-specific requirements and growth stage

$$F_{needed}=(N_{target}-N_{estimated})\times A_{crop} \qquad (6)$$

Where in Equetion (6) Fneeded is the amount of fertilizer needed, N_{target} is the target nitrogen level, $N_{estimated}$ is the estimated nitrogen level from the LCC, and A_{crop} is the area of the crop. This model forms the basis for a robust IoT-based system to manage nitrogen levels effectively, based on real-time analysis of leaf color using a digital Leaf Color Chart.

LIMITATIONS

Developing an Internet of Things (IoT)-based system for nitrogen management in agriculture involves addressing technical, economic, environmental, and societal challenges. Technical limitations are critical as they directly affect system functionality and reliability. Precision is paramount for sensors, but many commonly used sensors in agriculture have limitations in specificity and sensitivity, particularly in various field conditions. Precision is especially crucial for leaf color sensors to accurately detect nitrogen levels, even amidst slight fluctuations in greenness. Regular calibration of these sensors using standardized color charts, considering ambient lighting and installation angles, is necessary to ensure accuracy.

Environmental factors such as mud splashes, leaf wetness, and dust can obstruct sensor data, requiring regular cleaning and maintenance, which may be impractical on a large scale. Another technical challenge is integrating data from multiple sources. IoT systems in agriculture often combine data from soil sensors, weather stations, and plant sensors, necessitating complex image processing algorithms for crop health data from multispectral sensors. This can strain backend infrastructure, demanding robust systems for swift and accurate data processing.

In agriculture, real-time or near real-time data interpretation is crucial for prompt decision-making in IoT applications, such as adjusting irrigation systems or deploying fertilizers. Bandwidth limitations in remote farms can cause delays and reduce intervention effectiveness by hindering the transfer of large datasets to cloud-based systems. Reliable connectivity is essential for sensor networks in vast agricultural areas. Overcoming these constraints requires enhancing sensor technology and data fusion algorithm performance, along with improved rural connectivity or edge computing models for local data processing.

Scalable models, subsidies, and focused training can facilitate the adoption of new practices, while continuous support helps mitigate operational challenges. Leveraging IoT-based systems has the potential to significantly transform nitrogen management in agriculture by addressing technical, economic, environmental, and social hurdles effectively.

FUTURE DIRECTIONS

The future outlook for IoT-based frameworks in nitrogen management appears promising as the agriculture sector increasingly embraces novel technologies. There is considerable scope for technical advancements in sustainable agriculture, bearing significant implications. Prospective developments in sensor technology may emphasize refining precision, resilience, and selectivity across diverse environmental contexts. This could entail the advancement of nano-sensors capable of directly detecting and quantifying specific nitrogen molecules in soil or plant tissues. Furthermore, progress in sensor fusion methodologies may enable a holistic evaluation of plant health by amalgamating data from various sensors, potentially integrating soil moisture measurements with atmospheric data to optimize irrigation and fertilization strategies.

The integration of artificial intelligence (AI) and machine learning (ML) is poised to advance, offering increasingly sophisticated predictive analytics tailored for precision agriculture. Algorithms can be engineered to discern enduring data trends, thereby enhancing forecasts regarding the most efficacious nitrogen application rates and timings. These adaptive systems can anticipate fluctuating climate conditions, furnishing predictive insights to empower farmers in preemptively adjusting their methodologies based on projected weather patterns or environmental shifts.

Autonomous terrestrial and aerial robotic systems hold promise for multifarious tasks, encompassing soil profiling, data acquisition, and meticulous fertilizer dissemination. Advanced imaging technologies may be assimilated into drone platforms to afford comprehensive crop surveillance and targeted nutrient delivery, thereby curtailing wastage while optimizing productivity.

To surmount challenges associated with real-time data processing and bandwidth limitations, a wider adoption of edge computing methodologies could be pursued. This approach entails decentralized data processing proximal to the point of origination, thereby mitigating delays linked with data transmission to centralized cloud servers and augmenting the velocity of critical decision-making processes.

Conclusion

The integration of IoT technology with the Leaf Colour Chart (LCC) represents a notable progress in precision agriculture, namely in the field of nitrogen management. This combination improves the accuracy and effectiveness of nitrogen delivery, ensuring that fertilizers are utilized in the best possible way to promote crop development while minimizing both wastage and negative effects on the environment. Through the process of automating data collecting and analysis, this method effectively decreases labor expenses and enhances the precision of nitrogen control. It allows for ongoing surveillance across extensive regions, a task that would be unfeasible to do manually. Not only does this result in improved crop health and higher yields, but it also makes a substantial contribution to sustainable farming methods by minimizing fertilizer runoff and the accompanying environmental hazards. Overall, the combination of IoT with LCC represents a significant advancement in enhancing the sustainability and efficiency of agricultural processes.

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