# Smart Hydroponic Greenhouse Using Business Intelligence Tools and Deep Learning Algorithms

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**Abstract: Hydroponics is a soilless farming technique in which the plants are irrigated with a nutrient solution consisting of water and compounds necessary to provide all the essential elements for normal mineral nutrition. Increase in population, industrialization which has lead to pollution and change in climatic condition has pose a serious threat to food security. This paper therefore explores the integration of Deep Learning (DL) and Business Intelligence (BI) in smart hydroponic greenhouse systems, aiming to optimize cultivation through data-driven automation. A conceptual architecture is presented, highlighting the flow of information from sensor inputs and cameras, through a Raspberry Pi and IoT gateway, to a central database. ANNs, including classification and prediction models, process this data, enabling automated control of actuators and providing actionable insights through a BI dashboard. The discussion of findings, based on reviewed literature and the proposed architecture, reveals a strong trend towards leveraging advanced technologies for improved efficiency, accuracy, and productivity in hydroponic agriculture. The integration of deep learning for tasks like disease detection and yield prediction, coupled with BI for data visualization and decision support, underscores the potential of these technologies to revolutionize hydroponic practices. This research emphasizes the importance of data-driven approaches, IoT infrastructure, and closed-loop control systems in creating intelligent and sustainable greenhouse environments.**

***Keywords:*** *Hydroponics, Greenhouses, Deep Learning, Artificial Neural Network, Business Intelligence, Smart System.*

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## I. INTRODUCTION

Hydroponic greenhouses, enclosed structures typically made of plastic or glass (Baras, 2018; Singh et al., 2016), represent a revolutionary approach to plant cultivation. Unlike traditional agriculture that relies on soil, hydroponics involves growing plants in a nutrient-rich water solution. This soilless method offers significant advantages, particularly in regions where climate, soil quality, or land availability pose challenges to conventional farming (Son et al., 2020; Ifechukwude et al., 2022). By meticulously controlling environmental factors such as temperature, humidity, and nutrient levels, hydroponics enables the cultivation of a wide variety of crops in diverse locations, including urban areas.

Nigeria, like many developing nations, faces a growing food security crisis. A confluence of factors, including rapid population growth, the encroachment of oil exploration and industrialization, and the impacts of climate change, has led to a significant decline in arable land, soil fertility, and access to clean water resources (UN, 2016; Bardi & Palazzi, 2022). These challenges threaten agricultural productivity and exacerbate food shortages. Hydroponics emerges as a viable solution by offering a sustainable and efficient alternative to conventional farming, enabling food production in areas where traditional agriculture is no longer feasible.

While hydroponics presents a promising solution, effectively managing a hydroponic system requires meticulous attention to detail. Monitoring and controlling environmental factors such as water pH, temperature, nutrient levels, and dissolved solids are crucial for optimal plant growth. Manual monitoring and control can be labor-intensive, time-consuming, and prone to human error. To address these limitations, the development of "smart" hydroponic systems that incorporate advanced technologies is essential (Panwar et al., 2011; Bardi & Palazzi, 2022).

This paper therefore explores the integration of Deep Learning (DL) and Business Intelligence (BI) in smart hydroponic greenhouse systems, aiming to optimize cultivation through data-driven automation.

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➢ *Overview of a Smart Hydroponic System*

Soil plays a crucial role in traditional agriculture (Baras, 2018), providing plants with essential support, nutrients, and a habitat for beneficial microorganisms. However, hydroponics, a soilless cultivation technique, offers an alternative approach (Baras, 2018; Singh et al., 2016). As defined by Bardi & Palazzi (2022), hydroponic farming involves cultivating plants in a nutrient-rich water solution, providing all the essential elements for plant growth without the use of soil.

Hydroponics, while often perceived as a modern innovation, has ancient roots, with evidence found in Egyptian wall paintings (Raviv & Lieth, 2007). The term "hydroponics" itself originates from Greek words: "hydro" meaning water and "ponos" meaning labor (Khan et al., 2018). Essentially, it is a modern agricultural technique that replaces soil with a nutrient solution for crop production (Bridgewood, 2003; Hochmuth & Hochmuth, 2001).

Soil, typically the most favorable medium for crop growth, provides essential nutrients, air, and water for plant development (Khan et al., 2018). However, limitations of soil-based agriculture include the presence of disease-causing microorganisms, inappropriate soil responses, poor drainage, soil compaction, and soil degradation. Hydroponics offers a solution by eliminating these soil-related constraints, enabling more efficient and controlled plant growth.

One of the major advantages of hydroponic greenhouse cultivation is the efficient utilization of natural light. Light plays a crucial role in fruit development. In a hydroponic greenhouse, light falls evenly on both the upper and lower parts of the plant, leading to more uniform fruit development (Despommier, 2009). Hydroponics is particularly well-suited for cultivating high-value crops such as leafy greens, fruits, flowers, and fodder (RIRDC, 2001). Research has consistently demonstrated the benefits of hydroponic systems, including minimal pesticide use, increased yields, and water conservation (Resh & Howard, 2012; Arias et al., 2000; Buchanan et al., 2013; Koyama et al., 2013).

Hydroponics offers several advantages over traditional farming. It is soil-independent, making it flexible and portable. Cultivation is faster compared to traditional methods. Hydroponic systems require less space and can be grown in various locations, including urban areas. They are less susceptible to seasonal variations and require minimal pesticide and herbicide use. Furthermore, hydroponically grown crops are protected from soil-borne diseases and pests, facilitating easier isolation during experiments (Ke & Xiong, 2008; Wang et al., 2011; Suzui et al., 2009; Liu et al., 2012).

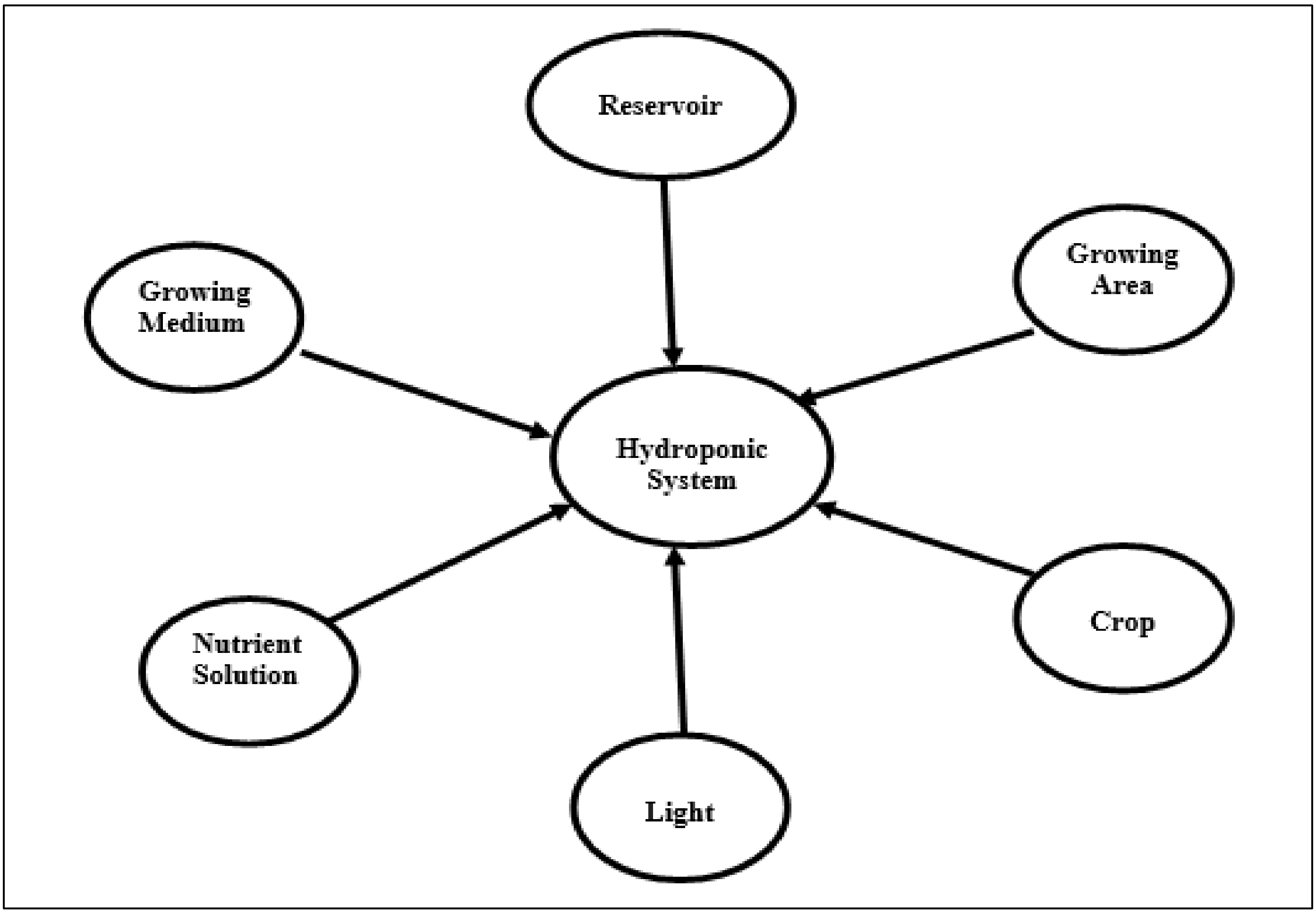


Fig 1 Components of Hydroponic System (Modu et al, 2020 and Alam et al, 2023)

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Hydroponic fertilizers typically contain six essential nutrients: N, P, S, K, Ca, and Mg, which are fed to the plants in balanced ratios (Kaewwiset & Yooyativong, 2017). Various growing media, such as wood chips, can be used in conjunction with water to create a hydroponic system (Muro et al., 2004). In closed or indoor hydroponic systems, light-emitting diodes (LEDs) and other artificial light sources are used to provide the necessary light for photosynthesis. Other critical factors to consider include ambient temperature, nutrient solution temperature, photoperiod, and air humidity (Gupta, 2004).

Components of a hydroponic system include the growing area/location, the specific crop being cultivated, the growing medium, nutrient solution, a reservoir for the nutrient solution, and a lighting system (Mudo *et al,* 2020). These systems can be operated automatically, with automated systems controlling factors such as temperature, pH level of the water, nutrient delivery, air conditioning, and humidity. Figure 1 shows the components of a hydroponic system.

Smart hydroponic systems represent a significant advancement in this field. Mudo et al. (2020) classified smart hydroponic systems into four main categories based on their level of automation, the tasks they automate, the type of automation, and the mode of control. These systems range from semi-automated systems, where only some components are automated, to fully-automated systems that handle all aspects of the growing process.

Smart hydroponic systems can be designed to perform various tasks, including system maintenance (hardware, consumables, security), crop cultivation (nutrient delivery, lighting, seedling management, harvesting), and system monitoring and reporting. By integrating advanced technologies such as sensors, automation, and artificial intelligence, smart hydroponic systems can optimize plant growth, improve resource utilization, and enhance the overall efficiency and sustainability of agricultural production.

- *Business Intelligence in Smart Hydroponic Greenhouse*

Business intelligence (BI) has the potentials of revolutionizing hydroponics, transforming it from a traditional cultivation method into a data-driven, high-performance agricultural practice. BI essentially automates data collection, analysis, and visualization, empowering growers with actionable insights for informed decision-making. This translates to enhanced operational efficiency and maximized profitability. (Bussa, 2023; Syed and Nampally, 2021; Solanki *et al*, 2024)

The core of BI in hydroponics involves collecting real-time data on critical parameters like temperature, humidity, nutrient levels, pH, and light intensity. Sensor networks and monitoring devices gather this data, providing a comprehensive picture of the growing environment. BI tools can then be used to analyze this data to identify trends, patterns, and potential issues (Ikegwu *et al*, 2022; Bussa, 2023). For example, historical data on environmental conditions and crop yields can be analyzed to determine optimal growing conditions for specific plants, leading to increased productivity and reduced resource waste.

BI empowers proactive management through predictive analytics (Udeh *et al*, 2024; Solanki *et al*, 2024; Omol *et al*, 2024). By analyzing historical data and identifying correlations between environmental factors and plant health, BI can forecast potential problems like nutrient deficiencies, pest infestations, or disease outbreaks. This allows growers to take timely interventions, minimizing losses and ensuring optimal plant growth. In essence, BI fosters data-driven decision-making, enabling growers to optimize resource allocation, improve operational efficiency, and enhance overall profitability (Abdel-Basset *et al*, 2024). From optimizing nutrient solutions and irrigation schedules to predicting market demand and identifying areas for improvement, BI plays a crucial role in transforming hydroponics into a highly efficient and sustainable agricultural practice.

## II. REVIEW OF RELATED WORKS

Several studies have explored the application of Deep Learning (DL) algorithms and Business Intelligence (BI) solutions in smart hydroponic greenhouses, aiming to enhance efficiency and productivity. While the direct combination of both DL and BI is still emerging, research highlights their individual contributions and the potential synergy when integrated.

Wongpatikaseree et al (2018) investigated the performance of 3 classical machine learning classifiers: decision tree, Naive Bayes, Multi-Layer Perception and one type of deep neural network in the detecting the freshness of vegetation harvested from a smart hydroponic system. The proposed system uses image processing and machine learning technologies to detect fresh and withered vegetables. The experiment shows that the decision tree (J48) model was found to have the best accuracy of 98:12%. This system can be used in harvesting and/or monitoring the health of crops grown in a hydroponic system

Alipio et al. (2017) developed a smart hydroponic system using Bayesian Networks (BN) to automate environmental control. Their system, which monitored and adjusted parameters like light intensity, pH, and electrical conductivity, resulted in a 66.67% yield increase compared to manual control. However, the system lacked control over crucial parameters like $CO_2$ and oxygen, and raised concerns regarding data security and transparency.

Asy'ari et al. (2023) utilized an ARIMA model for forecasting plant growth in hydroponic farms, demonstrating the potential of time series analysis in this domain. Their model, based on data collected via IoT and machine-to-machine communication, showed that the performance of ARIMA (2, 2, 1) time series forecasting model in predicting hydroponic plants' growth gives the smallest value of RMSE, MAE, and MAPE with 0.97, 0.94, and 0.04, respectively.

Raju et al (2022) implemented a mobile application integrated with an AI-based smart hydroponics expert system (AI-SHES) using IoT. Their system combined hardware for real-time data collection (NPK, sunlight, turbidity, pH, temperature, water level, and camera), a deep learning CNN model for nutrient level prediction and disease detection, and a mobile interface for farmer interaction. The obtained simulation results on disease detection and classification using proposed AI-SHES with IoT disclose superior performance in terms of accuracy, F-measure, precision and recall with 99.29%, 99.23%, 99.38% and 98.58% respectively. While achieving high accuracy (99.29%) in disease detection, the system, like Alipio et al. (2017), lacked control over key parameters and raised concerns about data security and energy consumption.

Rajkumar and Chachadi (2021) developed an automated hydroponic system with remote monitoring capabilities. Their system, using a sensor network, Arduino, Raspberry Pi, and a decision tree algorithm, maintained stable pH, EC, temperature, and humidity levels. However, they did not address system accuracy or anomaly detection for disease prevention.

Bulut and Hacıbeyoğlu (2023) explored the use of plant water and wastewater data in conjunction with various machine learning and deep learning algorithms (SVM, K-NN, Naive Bayes, Logistic Regression, Decision Trees, DNN, CNN, ANN, RNN) to evaluate plant growth. Their research indicated that DNNs achieved the highest success rate (99.7%), emphasizing the potential of machine learning in optimizing hydroponic agriculture. However, they did not consider yield performance, intrusion detection, or disease detection.

Rajkunwar et al. (2024) focused on plant disease and nutrient deficiency detection using image scrutiny techniques and CNNs. Their model, trained on substantial dataset, achieved 96% accuracy for disease detection and 87% for nutrient deficiency detection, showcasing the potential of AI-driven image recognition for real-time monitoring and intervention.

Tambakhe and Gulhane (2022) developed an intelligent crop growth monitoring system using IoT and machine learning. Comparing several regression models (SVR, Linear Regression, Lasso Regression, Decision Tree, Ridge Regression, Random Forest), they found that Random Forest provided the highest accuracy (95%) for predicting crop growth. Their system collected real-time data on various parameters (pH, EC, TDS, water temperature, temperature, and humidity) and stored it on Firebase.

Mashumah et al. (2018) developed a Nutrient Film Technique (NFT) hydroponic system using fuzzy logic control to regulate electrical conductivity (EC) levels. Their system integrated image processing (via webcam) to determine plant saturation and adjust EC setpoints, demonstrating the potential of combining image-based analysis with fuzzy control. While achieving reasonable accuracy in EC maintenance, the system's reliance on saturation values and the inherent error in water volume measurement (15.6%) present limitations.

JSM and Sridevi (2014) also employed fuzzy logic, but in conjunction with a genetic algorithm (GA), for pH control in a hydroponic system. Their approach aimed to address the limitations of traditional PID controllers by using a Mamdani fuzzy inference system (FIS) to evaluate nutrient solution quality and then employing a GA to optimize valve control. While the combined FIS-GA approach showed improved performance compared to fuzzy or PID controllers alone, the system's use of a drain valve raises concerns about nutrient waste.

Ayala-Silva and Beyl (2002) investigated the use of a multilayer perceptron (MLP) neural network for classifying nutrient deficiencies in wheat using hyperspectral data. Their research demonstrated the potential of ANNs for automated nutrient management, achieving high classification accuracy for deficiencies in nitrogen, phosphorus, potassium, and calcium. However, the authors acknowledge the challenge of obtaining sufficient training data for other crops.

Gartphol et al. (2018) developed predictive models for lettuce quality using data from an IoT-based hydroponic farm. While their focus was on regression models derived from environmental and growth data, the study highlights the importance of data collection and analysis in smart hydroponics. The challenges they encountered with measurement errors underscore the need for robust sensor technologies and data processing techniques..

Pancić et al. (2023) investigated the influence of BI on firm performance, considering the mediating roles of big data analytics and blockchain adoption. Their finding showed that BI has a direct and significant positive influence on firm performance.

## III. METHODOLOGY

A review of related literature was conducted to explore the intersection of smart hydroponic greenhouses, Business Intelligence (BI) tools, and Artificial Neural Networks (ANNs). Thirty journal articles were initially identified through searches in scholarly databases including Google Scholar, ScienceDirect, IEEE Xplore, and ResearchGate. These sources were queried using keywords related to smart hydroponic greenhouse systems, BI solutions, and the impact of these technologies on business or firm performance. After a preliminary screening, sixteen papers were excluded as they did not specifically address smart hydroponic greenhouse systems or the application of BI solutions in this context.

The remaining fourteen papers, which directly related to the research topic, were then selected for a detailed review. This focused review examined how these studies explored the use of BI and ANNs in optimizing various aspects of smart hydroponic greenhouse operations, including but not limited to environmental control, resource

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management, yield prediction, and disease detection, and how these technologies contributed to improved performance.

## IV. RESULTS AND DISCUSSION

### *A. Results*

Table 1 summarizes the application and performance of various machine learning and artificial intelligence technologies in smart hydroponic greenhouse systems

Figure 2 illustrates the distribution of research focus areas within the domain of smart hydroponic systems, highlighting key applications of technology such as image-based detection, disease and nutrient deficiency detection, yield prediction, and automated control/resource optimization.

Figure 3 depicts the yearly publication trend relating to smart hydroponic greenhouse systems using deep learning algorithms from 2014 to 2024.

Figure 4 presents a proposed conceptual architecture for a smart hydroponic greenhouse using business intelligence tools and artificial neutral network.

Table 1 Application and Performance of various Deep Learning and AI technologies in Smart Hydroponic Greenhouse Systems

| **Authors** | **Year** | **Developed System/ Model** | **Technology Used** | **Findings** |
|---|---|---|---|---|
| Wongpatikaseree *et al* | 2018 | Image-based crop freshness detection system | Decision Tree, Naive Bayes, Multi-Layer Perception, DNN | DT has the higest performance with 98.2% accuracy |
| Alipio et al. | 2017 | Automated control system | Bayesian Networks | 66.67% yield increase |
| Asy'ari et al. | 2023 | Plant Growth Prediction | ARIMA model | RMSE of 97%, MAE of 94%, and MAPE of 0.04 |
| Raju *et al* | 2023 | Nutrient level prediction and Disease detection | CNN Model | 99.29% accuracy for disease detection |
| Rajkumar and Chachadi | 2021 | Automated control system | IoT Sensors and Decision Trees | maintained stable pH, EC, temperature, and humidity levels |
| Bulut and Hacıbeyoğlu | 2023 | Plant Growth Prediction | SVM, K-NN, Naive Bayes, Logistic Regression, Decision Trees, DNN, CNN, ANN, RNN | DNNs achieved the highest success rate of 99.7% |
| Rajkunwar et al | 2024 | Plant disease detection and nutrient deficiency detection | Image scrutiny techniques and CNNs | 96% accuracy for disease detection and 87% for nutrient deficiency detection, |
| Tambakhe and Gulhane | 2022 | Crop growth monitoring system | SVR, Linear Regression, Lasso Regression, Decision Tree, Ridge Regression, Random Forest | Automated time series data collection stored in Firebase. Also Random Forest provided the highest accuracy (95%) for predicting crop growth |
| Mashumah *et al* | 2018 | Electrical Conductivity (EC) Level Regulation | image-based analysis with fuzzy logic | EC accuracy limited by saturation and volume error. |
| JSM and Sridevi | 2014 | pH control system | fuzzy logic with a genetic algorithm | The combined FIS-GA approach showed improved performance compared to fuzzy or PID controllers alone |
| Ayala-Silva and Beyl | 2002 | Nutrient Deficiency Classification | multilayer perceptron (MLP) neural network | Achieved high classification accuracy for deficiencies in nitrogen, phosphorus, potassium, and calcium. |

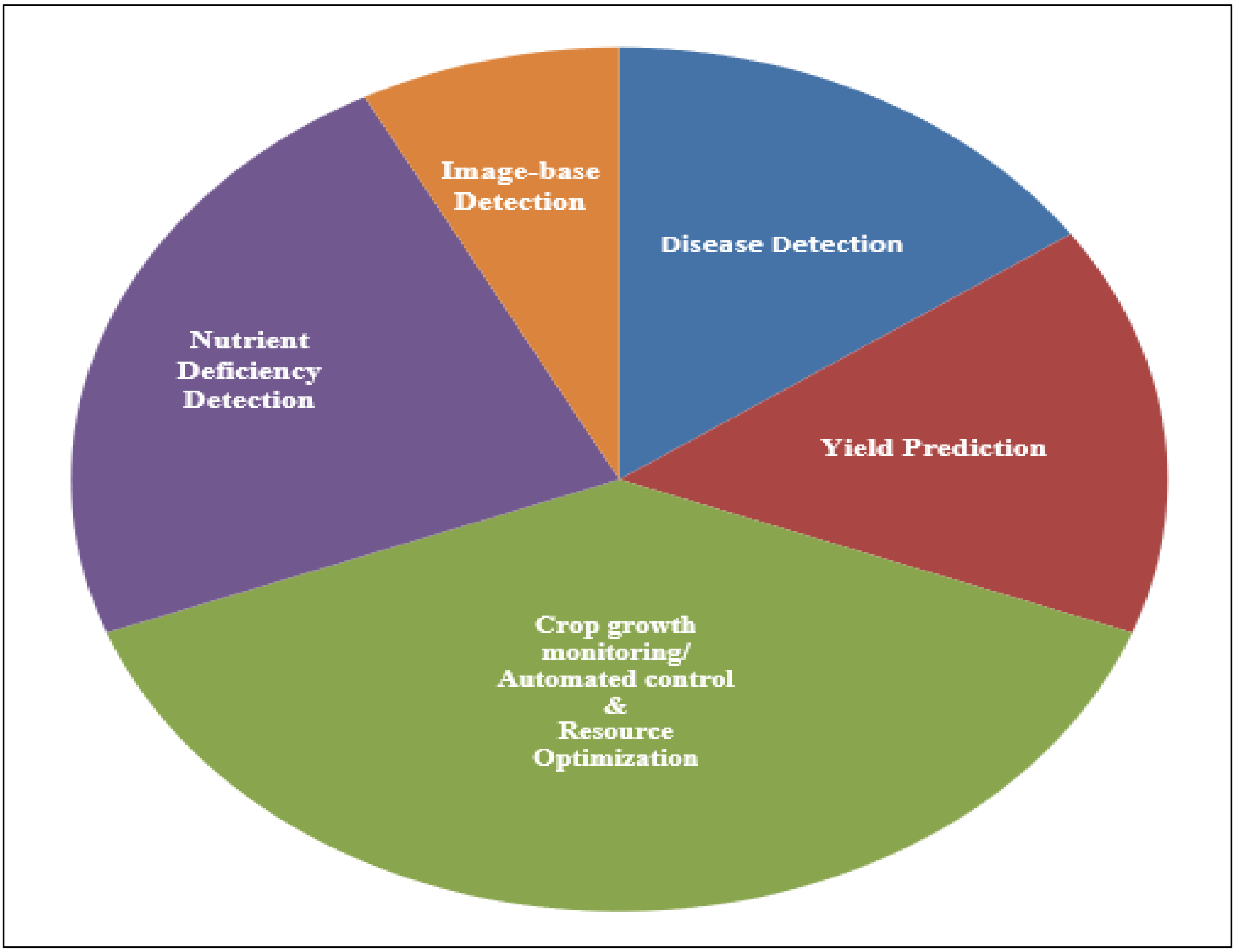


Fig 2 Distribution of Research Focus Areas within the Domain of Smart Hydroponic Systems

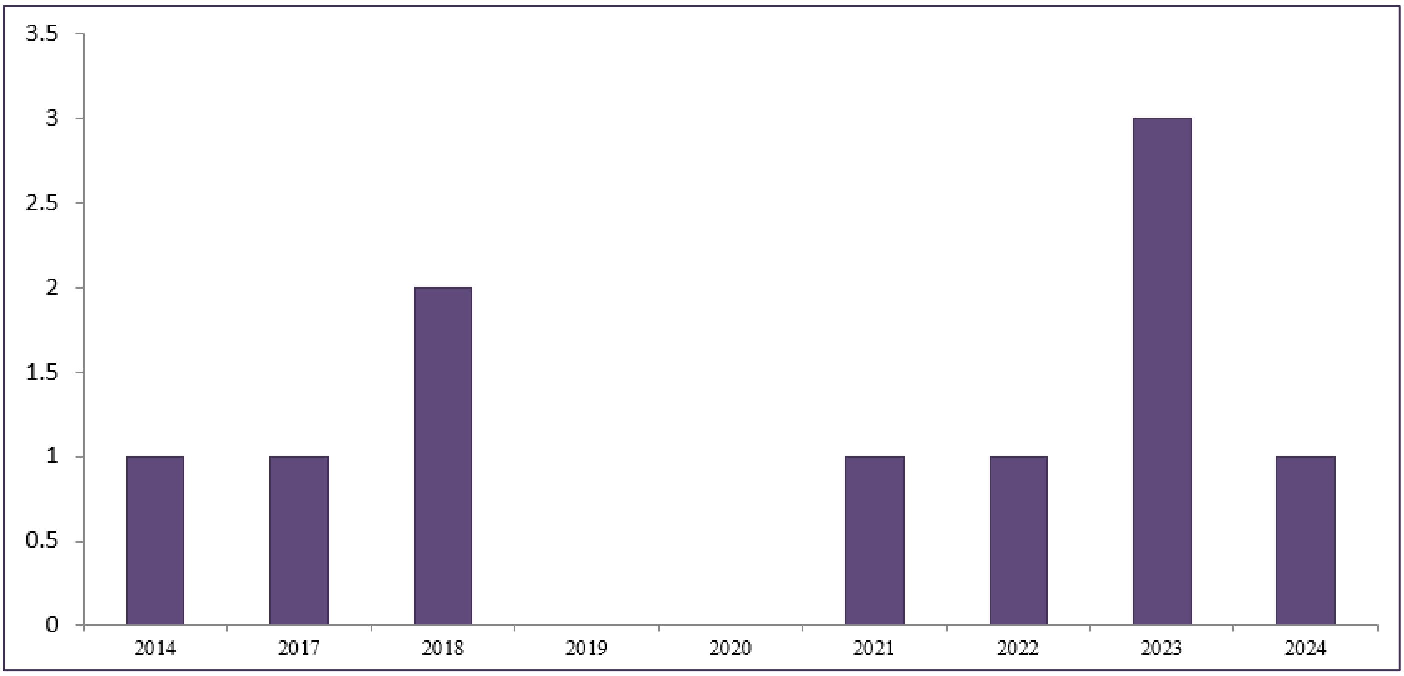


Fig 3 Publication Trend relating to Smart Hydroponic Greenhouse Systems using Deep Learning Algorithms

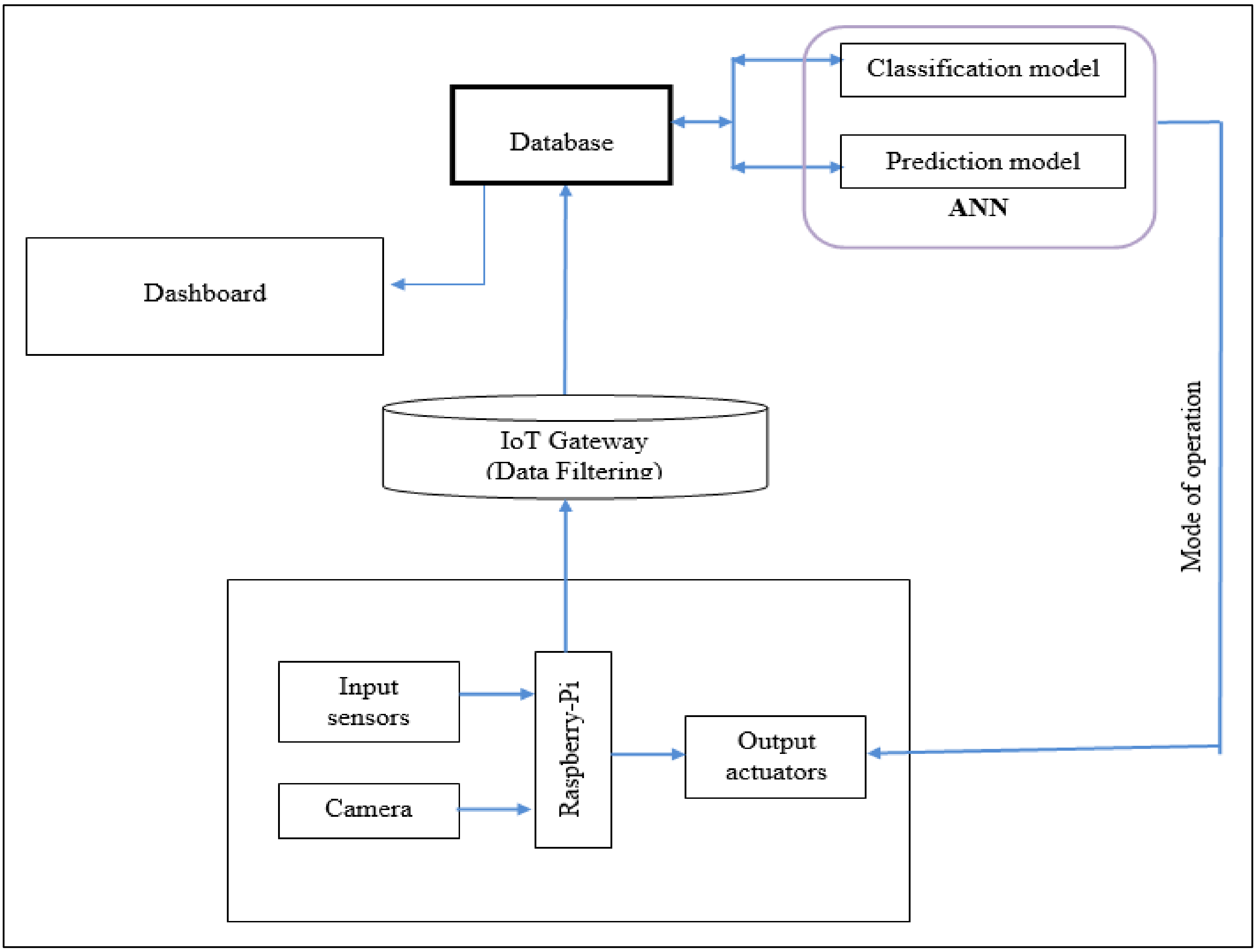


Fig 4 Proposed Conceptual Architecture for a Smart Hydroponic Greenhouse System using Deep Learning and Business Intelligence Solution

*B. Discussion of Findings*

The collective findings from the reviewed literature, encompassing both individual studies and broader trends, highlight a significant and evolving landscape in smart hydroponic greenhouse systems. A clear direction emerges: the integration of advanced technologies, particularly machine learning (ML), artificial intelligence (AI), and the Internet of Things (IoT), is revolutionizing hydroponic agriculture.

➢ *Technological Advancements and their Impact*

The reviewed studies demonstrate the tangible benefits of these technologies. Image-based analysis, as evidenced by Wongpatikaseree et al. (2018), showcases the potential for automated quality assessment, leading to real-time monitoring and reduced manual labor. Automated control systems, exemplified by Alipio et al. (2017) and Rajkumar and Chachadi (2021), significantly enhance yield and maintain stable growing conditions. Predictive modeling, through time-series analysis (Asy'ari et al., 2023) and deep learning (Bulut and Hacıbeyoğlu, 2023), enables optimized resource allocation and anticipates future growth patterns. Deep learning, notably Convolutional Neural Networks (CNNs) in Raju et al. (2023) and Rajkunwar et al. (2024), effectively automates disease and nutrient deficiency detection, safeguarding plant health. Data-driven crop growth monitoring (Tambakhe and Gulhane, 2022) and intelligent control systems using fuzzy logic (Mashumah et al., 2018; JSM and Sridevi, 2014) further illustrate the diverse applications and benefits of these technologies.

➢ *Research Focus and Trends*

Result in figure 2 reveals a strong emphasis on disease detection, yield prediction, and automated control/resource optimization. This distribution underscores the critical importance of these areas in ensuring the success and sustainability of hydroponic agriculture. The prevalence of research on automated systems indicates a clear trend towards minimizing human intervention and maximizing efficiency. Furthermore, the integration of image-based analysis and advanced sensor technologies across multiple research areas highlights the increasing sophistication of hydroponic systems.

- **Image-Based Analysis and Quality Assessment:** Wongpatikaseree et al. (2018) effectively showcased the power of image-based analysis combined with ML for crop quality assessment. Their finding that Decision

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Trees (DT) achieved 98.2% accuracy in freshness detection highlights the feasibility of automating quality control processes. This indicates a potential for real-time monitoring of crop health and timely harvesting, reducing manual labor and ensuring consistent product quality.

- **Automated Control and Yield Optimization:** Alipio et al. (2017) demonstrated the significant impact of automated control on yield. Their Bayesian Network-based system achieved a 66.67% yield increase by precisely managing environmental parameters. This finding underscores the importance of intelligent control systems in optimizing growing conditions and maximizing productivity in hydroponic settings. Rajkumar and Chachadi (2021) further supported this, showing that IoT sensors and decision trees can maintain stable environmental parameters, essential for healthy plant growth.
- **Predictive Modeling and Time Series Analysis:** Asy'ari et al. (2023) and Bulut and Hacıbeyoğlu (2023) focused on predictive modeling, particularly for plant growth. Asy'ari et al. achieved high accuracy in predicting plant growth using an ARIMA model, demonstrating the potential of time-series analysis for forecasting crop development. Bulut and Hacıbeyoğlu (2023) expanded on this by comparing various ML and deep learning models, finding that Deep Neural Networks (DNNs) achieved an impressive 99.7% success rate. These studies highlight the potential of predictive analytics to optimize resource allocation and anticipate future growth patterns.
- **Disease and Nutrient Deficiency Detection using Deep Learning:** Raju et al. (2023) and Rajkunwar et al. (2024) explored the application of Convolutional Neural Networks (CNNs) for disease and nutrient deficiency detection. Raju et al. achieved 99.29% accuracy in disease detection, while Rajkunwar et al. reported 96% accuracy for disease detection and 87% for nutrient deficiency detection. These findings highlight the effectiveness of deep learning in automating plant health monitoring. The ability to detect diseases and nutrient deficiencies early can prevent crop losses and ensure optimal plant health.
- **Data-Driven Crop Growth Monitoring and Regression Models:** Tambakhe and Gulhane (2022) focused on crop growth monitoring using various regression models. They found that Random Forest achieved the highest accuracy (95%) in predicting crop growth. Their system, which stored real-time data in Firebase, demonstrates the potential of IoT and cloud-based data storage for continuous monitoring and analysis.
- **Intelligent Control Systems:** Mashumah et al. (2018) and JSM and Sridevi (2014) explored the use of fuzzy logic for intelligent control. Mashumah et al. used fuzzy logic for EC level regulation, while JSM and Sridevi combined fuzzy logic with a genetic algorithm for pH control. Both studies demonstrate the potential of fuzzy logic to handle complex and dynamic systems, but also highlight the challenges related to sensor accuracy and system design. Mashumah et al. showed that EC accuracy was limited by saturation and volume error, and JSM and Sridevi's approach, while improving upon pure fuzzy or PID control, still has potential for improvement.
- **Nutrient Deficiency Detection and Classification:** Ayala-Silva and Beyl (2002) demonstrated the potential of Multilayer Perceptron (MLP) neural networks for classifying nutrient deficiencies using hyperspectral data. Their research showed high classification accuracy, highlighting the potential of ANNs for automating nutrient management. However, they also noted the challenge of obtaining sufficient training data for other crops.

➢ *Publication Trends and Research Dynamics*

Result from figure 3 reveals that smart hydroponic greenhouse system is a dynamic and evolving field. The fluctuating publication rate suggests periods of growth and stasis, reflecting the ebbs and flows of research funding, technological advancements, and practical applications. The significant surge in 2023 indicates a growing recognition of ANNs' potential, while the projected decline in 2024 suggests the need for sustained research and development.

➢ *Conceptual Architecture for a Smart Hydroponic Greenhouse System using Deep Learning and Business Intelligence Solution*

Figure 4 presents a conceptual architecture for a smart hydroponic greenhouse system, demonstrating a clear focus on data-driven optimization through the integration of Artificial Neural Networks (ANNs) and Business Intelligence (BI). The system initiates with a comprehensive data acquisition layer, comprising "Input Sensors" and a "Camera." These components gather crucial environmental and visual data, forming the foundation for subsequent analysis. A "Raspberry Pi" acts as the central processing unit, processing the incoming data and facilitating communication with the "IoT Gateway." This gateway ensures seamless data transfer to the "Database," which serves as the system's central repository, storing sensor readings, images, and processed information.

The core intelligence of the system resides within the "ANN" module, which houses "Classification Model" and "Prediction Model." The Classification Model, likely a Convolutional Neural Network (CNN), analyzes camera images for disease detection and plant health assessment. The Prediction Model, potentially a Recurrent Neural Network (RNN), forecasts yields and environmental conditions. The "Mode of Operation" feedback loop signifies that the ANN's outputs directly influence the system's control. Subsequently, "Output Actuators," controlled by the Raspberry Pi, adjust environmental parameters based on the ANN's outputs, enabling automated optimization. The "Dashboard" serves as the BI component, providing a user interface for visualizing data and monitoring system performance, translating raw data and model outputs into actionable insights for growers.

This architecture emphasizes a data-driven approach, utilizing data collected from sensors and cameras to train

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ANN models and inform decision-making. The integration of deep learning enhances automation and precision through complex tasks like image analysis and predictive modeling. The IoT infrastructure facilitates real-time monitoring and control, while the BI dashboard empowers growers with actionable insights. The closed-loop control system, facilitated by the feedback between the ANN and actuators, enables automated adjustments, optimizing growing conditions and minimizing human intervention. While the architecture provides a strong conceptual framework, it could be further enhanced by including details on specific ANN models, data preprocessing steps, scalability and security considerations, and power management. Overall, this architecture demonstrates the potential of integrating deep learning and business intelligence, orchestrated through an IoT infrastructure, to significantly enhance efficiency, productivity, and sustainability in hydroponic agriculture.

## V. CONCLUSION

This research has demonstrated the significant potential of integrating Deep Learning (DL) algorithms and Business Intelligence (BI) tools into smart hydroponic greenhouse systems. The reviewed literature and the proposed conceptual architecture highlight the transformative impact of these technologies on modern agriculture. By leveraging sensor data, image analysis, and predictive modeling, DL algorithms enable automated control, disease detection, and yield optimization. BI tools, through user-friendly dashboards, provide growers with actionable insights for informed decision-making. The proposed architecture, utilizing a Raspberry Pi, IoT gateway, and a central database, facilitates a data-driven approach to hydroponic cultivation. The integration of these technologies addresses the growing challenges of food security, particularly in regions facing climate change and limited arable land. The findings emphasize the importance of data-driven approaches, IoT infrastructure, and closed-loop control systems in creating intelligent and sustainable greenhouse environments.

Future endeavors should focus on developing robust and scalable Deep Learning models, enhancing Business Intelligence dashboards with real-time analytics, and investigating advanced sensor technologies. Prioritizing energy efficiency, data security, and interdisciplinary collaboration is crucial, alongside conducting field trials and developing user training programs. Standardizing data collection and exploring economic feasibility will further facilitate widespread adoption and contribute to global food security.

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