Development of an ESP32-Based Fuzzy Logic Smart Farming Monitoring System for Enhanced Agricultural Productivity

Mukesh Kumar Sinha[1], Dr. Rajesh Kumar Tiwari[2]

[1]Research Scholar, Mathematics, BBMKU, Dhanbad, Jharkhand, India
[2]Associate Professor, Mathematics, BBMKU, Dhanbad, Jharkhand, India

1. Abstract
The study outlines a new strategy for increasing agricultural productivity through the development and application of a fuzzy logic-controlled smart farming monitoring system. To continuously evaluate environmental factors, the system integrates a variety of sensors, including water level, light intensity, soil moisture, temperature, and humidity. According to experimental testing of the system output, the developed model's accuracy and efficiency in predicting and operating the water pump are 96.5% and 95.3%, respectively. With a 98.7% water pump operation rate, the model has proven to be highly reliable and responsive, with the system identifying the need for modification within one minute of the altered setting. It is now clear that fuzzy logic is the most effective method when compared to either the current farmer strategy or an alternative control design. Specifically, it guarantees accuracy, minimizes wasteful inputs, lowers labour costs, and lessens the risk of malpractice, all of which contribute to the system's superiority. It follows that fuzzy logic technology has the potential to revolutionize the traditional method of agricultural management. It enables the development of waste-avoidance and risk-proof strategies, enabling sustainable performance in the face of shifting environmental pressures.

Keywords: Smart farming, Fuzzy logic control, Sensor technology, Agricultural productivity, Environmental monitoring

2. Introduction
Agriculture in the twenty-first century faces the dual challenge of increasing food production while simultaneously addressing climate change, resource scarcity, and environmental degradation. Traditional farming practices, which rely heavily on manual decision-making and fixed operational schedules, often lead to inefficient use of water, energy, fertilizers, and labor. To overcome these limitations, smart farming also known as precision agriculture has emerged as a promising solution by integrating sensor technology, Internet of Things (IoT) platforms, automation, and data-driven decision-making systems. Such technologies enable continuous monitoring of environmental parameters and support timely, informed control actions that improve productivity while promoting sustainability.
Recent advances in sensor networks and IoT-based agricultural systems have demonstrated the potential for real-time monitoring of critical parameters such as temperature, humidity, soil moisture, light intensity, and water level. However, agricultural environments are inherently uncertain, nonlinear, and dynamic, making conventional control techniques insufficient for reliable decision-making under varying

conditions. In this context, fuzzy logic control has gained increasing attention due to its ability to handle imprecision and uncertainty using human-like reasoning. By employing linguistic variables, membership functions, and rule-based inference, fuzzy logic systems provide flexible and adaptive control strategies suitable for complex agricultural processes such as irrigation scheduling, nutrient management, and pest control. Building on these developments, the present study proposes the design and implementation of a smart farming monitoring system based on an ESP32 microcontroller integrated with a fuzzy logic control algorithm. The system incorporates multiple environmental sensors to continuously collect real-time data from the agricultural field and transmit it to a cloud-enabled platform for analysis and monitoring through a user-friendly interface. The fuzzy logic controller processes sensor inputs to make autonomous decisions regarding water pump operation, thereby optimizing irrigation while minimizing resource wastage. Unlike traditional farmer-driven or rule-based approaches, the proposed system dynamically adapts to changing environmental conditions and crop requirements. [1] Prathibha et al. (2017) demonstrated that modern monitoring systems can improve agricultural efficiency without degrading natural resources. [2] Preetha et al. (2023) highlighted the role of intelligent optimization techniques in reducing resource wastage in agricultural networks. [3] Guo et al. (2020) showed that advanced computational approaches can support sustainable crop management through accurate decision-making. [4] Dimatira et al. (2017) further emphasized that intelligent control techniques such as fuzzy logic can support environmentally responsible farming practices. Precision agriculture, sometimes referred to as smart farming, is one substitute. In order to maximize resource efficiency and optimize the agricultural production process, it makes use of technologies like the Internet of Things. Automation, IoT devices and data, and sensors enable smart farming. Information from multiple sensors and control systems placed in the field or greenhouse is gathered by the system using a central hub. After processing and analysing the data, the computer system instructs the field or greenhouse's actuator with the necessary commands. This system uses a smartphone application to send data and alarms to the manager or owner. Smart farming, also known as precision agriculture, integrates automation, sensor networks, and Internet of Things (IoT) technologies to optimize agricultural operations. [5] Srinivasan et al. (2024) proposed that decision-support systems based on artificial intelligence can significantly improve operational efficiency in agriculture. [6] Devikala et al. (2024) demonstrated the effectiveness of fuzzy logic controllers in automated systems using IoT platforms. [7] Paraforos et al. (2022) discussed the importance of standardized communication protocols for integrating smart agricultural equipment. [8] Akbar et al. (2020) showed that IoT-based monitoring systems enhance productivity and reduce manual intervention in farming environments.

The study's goal is to create and evaluate a smart farming monitoring system with fuzzy logic control. Based on the data, the system will automatically evaluate the condition of the plant and the surroundings thanks to a collection of intelligent, self-governing sensors. The farmer will receive the data and analysis findings through a smartphone application. Equipment and management arrangements will be created using data from the system sensors. In contrast to a traditional approach, this one is being tested in practice and responds to the major trends in agriculture today, which makes it novel. The study is significant because it has the potential to improve the efficiency and sustainability of agriculture.

The paper is organized as follows. Section 2 reviews the relevant literature on agricultural contamination, smart farming approaches, and applications of fuzzy logic in agriculture. Section 3 describes the fuzzy logic–based smart farming methodology, including the system architecture, data collection procedure, and mathematical formulations used for decision-making and control. Section 4 present the experimental results and their detailed discussion, highlighting the performance and effectiveness of the proposed system. Finally, Section 5 concludes the paper and provides recommendations for sustainable and efficient agricultural practices.

2. Literature Review

One solution to the problems facing modern agriculture is smart farming. It might have the power to completely alter farming practices and the agricultural management system. The system can deploy monitoring operational data on farms because it is based on sensor technology, IoT devices, and data analytics. Sensors for temperature, humidity, soil moisture, light intensity, and water level are frequently used to gather information and keep an eye on crops, soil, and environmental conditions. These sensors are typically found in smart farming systems, which allow farmers to monitor data in real-time and promptly take appropriate action to optimize operations and maximize yields. Sensor-based monitoring systems play a critical role in smart farming by enabling real-time observation of environmental and crop conditions. [9] Srinivasan et al. (2024) demonstrated that sensor fusion improves data reliability in intelligent agricultural systems. [10] Ferehan et al. (2022) emphasized the role of predictive analytics combined with IoT in improving farm management decisions. [11] Rakhra et al. (2022) applied machine learning techniques to sensor data for improving operational planning in agriculture. [12] Raghuvanshi et al. (2022) highlighted the importance of secure and reliable sensor networks for smart irrigation systems.
In smart farming solutions, fuzzy logic control systems are becoming more and more common. By comparing the brightness of light bulbs or clouds, the technology enables decision-making. Because agricultural environmental conditions are unpredictable, unknown, and subject to change, fuzzy logic algorithms can be used. As a result, among other agricultural duties, they can be applied to pest control, nutrient management, and irrigation scheduling. Fuzzy logic can be used in smart farming to optimize resource use and agricultural operations. Fuzzy logic control systems are increasingly adopted in smart farming applications due to their ability to handle uncertainty and imprecise environmental data. [13] Sivakumar et al. (2018) demonstrated the effectiveness of fuzzy-based optimization in engineering systems. [14] Phasinam et al. (2022) discussed the applicability of fuzzy logic in IoT-enabled smart farming environments. [15] Kim et al. (2018) successfully implemented fuzzy inference mechanisms for crop disease prediction in smart agriculture. [16] Ather et al. (2022) showed that artificial intelligence techniques, including fuzzy logic, can optimize resource utilization in farming systems.
Smart farming has been the subject of extensive research. Numerous studies have demonstrated its ability to boost resilience, sustainability, and yields. The technology has been examined in relation to multi-sensors, pressure-sensitive seats, and ammonia sensors. Data analytics, automation, and decision support systems have all been the subject of other studies. To address present issues and advance the systems' implementation, more research must be done. The primary issues with smart farming are interoperability, scalability, and cost. To support the technology and create a sustainable and food-secure system for future generations, more innovation in the field is required. Despite the growing adoption of smart farming technologies, several challenges remain, including scalability, interoperability, and implementation cost. [17] Arun Prakash et al. (2020) emphasized the need for robust material and system performance in agricultural technologies. [18] Lal et al. (2022) highlighted challenges related to data accuracy and classification in sensor-based agricultural systems. [19] Shukla et al. (2022) discussed integration issues in IoT-based agricultural and healthcare applications. [20] Verdouw et al. (2019) proposed an architectural framework to address interoperability and scalability in IoT-based farming systems.

In order to optimize irrigation scheduling, nutrient supply, and pest control at an agricultural site, this research is framed as the development and implementation of a smart farming monitoring system using a fuzzy logic control system that would incorporate various sensors for monitoring environmental parameters like temperature, humidity, soil moisture, light intensity, and water level. The monitoring system would use variations of imprecise reasoning. The proposed system integrates sensor technology and fuzzy logic control to optimize irrigation, nutrient management, and pest control operations. [21] Sivakumar et al. (2021) demonstrated that process optimization techniques can significantly enhance system performance. [22] Mohammed Thaha et al. (2023) explored intelligent coordination strategies that support autonomous decision-making systems. [23] Veena et al. (2019) highlighted the importance of automated monitoring systems in improving operational efficiency.

The primary focus of the research is on using data and cutting-edge technology to improve agricultural productivity and sustainability. The system would be created and explained in the current work, but it could be further examined to maximize its effectiveness and identify possible application areas. Future advancements in smart farming systems require improved hardware efficiency and faster computational methods. [24] Ariunaa et al. (2022) proposed high-speed digital processing techniques that can support real-time agricultural monitoring. [25] Preetha et al. (2021) discussed decentralized data management approaches for large-scale intelligent systems. [26] Chamara et al. (2022) reviewed the evolution and future scope of Ag-IoT systems for crop and environmental monitoring. [27] Ahmad et al. (2022) demonstrated the potential of IoT–fog architectures for scalable and secure smart system applications.

3. Methodology

The overall working architecture of the proposed smart farming system is illustrated in Fig. 1. In order to ensure that a complete smart farming monitoring system is accomplished, this study made use of sensor technology, the ESP32 microcontroller, cloud communication, and fuzzy logic control algorithm. Installing a variety of sensors to help measure various environmental parameters was the first step in the hardware assembly of the smart farming monitoring system. In particular, sensors for temperature, humidity, soil moisture, light intensity, and water level were positioned in various locations to allow for the collection of data on the crops' development and health in real time. These sensors were chosen because of their accuracy, dependability, and compatibility with the ESP32 microcontroller. Programming was the next step, which was required to enable communication with each sensor and allow for the periodic collection of data. Instead of acting as a bridge between the sensors and GPRS, the ESP32 took on the function of other microcontrollers, processing the data gathered and directing system control using a fuzzy logic algorithm. To lower the likelihood that data would be processed, it made use of error and exception handling procedures.

As a result, the fuzzy logic control algorithm was also created to evaluate sensor data and guarantee well-informed choices about pest control, nutrient application, and irrigation. Furthermore, it was predicated on a set of linguistic variables, membership functions, and fuzzy rules to define the operations and decision-making in cases where the given data is imprecise or fuzzy. The algorithm's primary responsibility was to automatically regulate the system to modify the frequency of irrigation, the quantity of nutrients to be applied to the crops, and the level of pest control based on real-time data and inspection findings. [27] Sinha and Tiwari (2024a) demonstrated that fuzzy logic–based disease detection systems significantly improve early diagnosis and management of crop diseases in precision agriculture. [28] Sinha and Tiwari (2024b) provided a comprehensive survey highlighting the widespread adoption of fuzzy logic techniques across irrigation, pest management, soil analysis, and yield prediction in modern agriculture. Another essential component of the monitoring system was communication, and the cloud needed to be set up. The ESP32 was connected via Bluetooth or Wi-Fi wireless communication when data analysis from the cloud was required. Every fifteen minutes, data packets were transmitted, and they included sensor data, system status, control action, and cloud storage for later use. Fig. 1. illustrates how the suggested system operates in its entirety.

$$\mu_A x = \begin{cases} 0, & x < b \\ \dfrac{x-a}{b-a}, & b \le x \le c \\ 1, & x > c \end{cases} \tag{1}$$

$$\mu_A x = \begin{cases} 1, & x < a \\ \dfrac{c-x}{c-b}, & a \le x \le b \\ 0, & x > b \end{cases} \tag{2}$$

$$I = f(T, H, M) \tag{3}$$

$$T = Temperature, H = Humidity, M = Soil\ moisture, I = Irrigation\ control\ output.$$

equations (1) – (3) formalize the fuzzification and inference process, with variables defined as temperature (T), humidity (H), soil moisture (M), and irrigation control output (I). The fuzzy logic model's linguistic variables and membership functions are designed to reflect qualitative environmental states (e.g., low, medium, high). Fuzzy rules encapsulate expert knowledge, such as "increase irrigation frequency if temperature is high and soil moisture is low."

The system's dataset comprises 3,422 cloud-stored sensor readings collected over several years. This dataset informs the fuzzy logic model's training and validation, optimizing membership functions and rule weights through heuristic methods like genetic algorithms and gradient descent. The trained model generates real-time irrigation and management recommendations based on current sensor data.

In the cloud environment, incoming data was analysed using the data analytic method in order to draw conclusions, make inferences, and review system trends appropriately. It's possible that machine learning algorithms could have improved the system's resilience and enabled more precise data analytics for the best possible decision-making. The final interface was created as a graphic user to allow farmers to remotely monitor the system and notify others when issues arose. The conceptual design of the proposed fuzzy logic controller is supported by earlier work on adaptive fuzzy inference systems for agricultural optimization. [29] Sinha and Tiwari (2024c) showed that ANFIS-based models can effectively optimize soil remediation parameters, thereby improving decision accuracy under uncertain environmental conditions.

3.1 Dataset used in this research

Using a dataset made up of the parameters associated with plant growth and health maintenance, a fuzzy logic model was created. Sensor readings for temperature, humidity, soil moisture, light intensity, and water level are included in the dataset. The model has processed 3422 cloud-stored readings over the past few years. The model gained knowledge of the particulars of the agricultural environment by examining the dynamics of these readings. The reason for this is that sensors record the changes and variations and send the data to the system. Thus, the model learned how to carry out routine tasks like crop irrigation and

International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

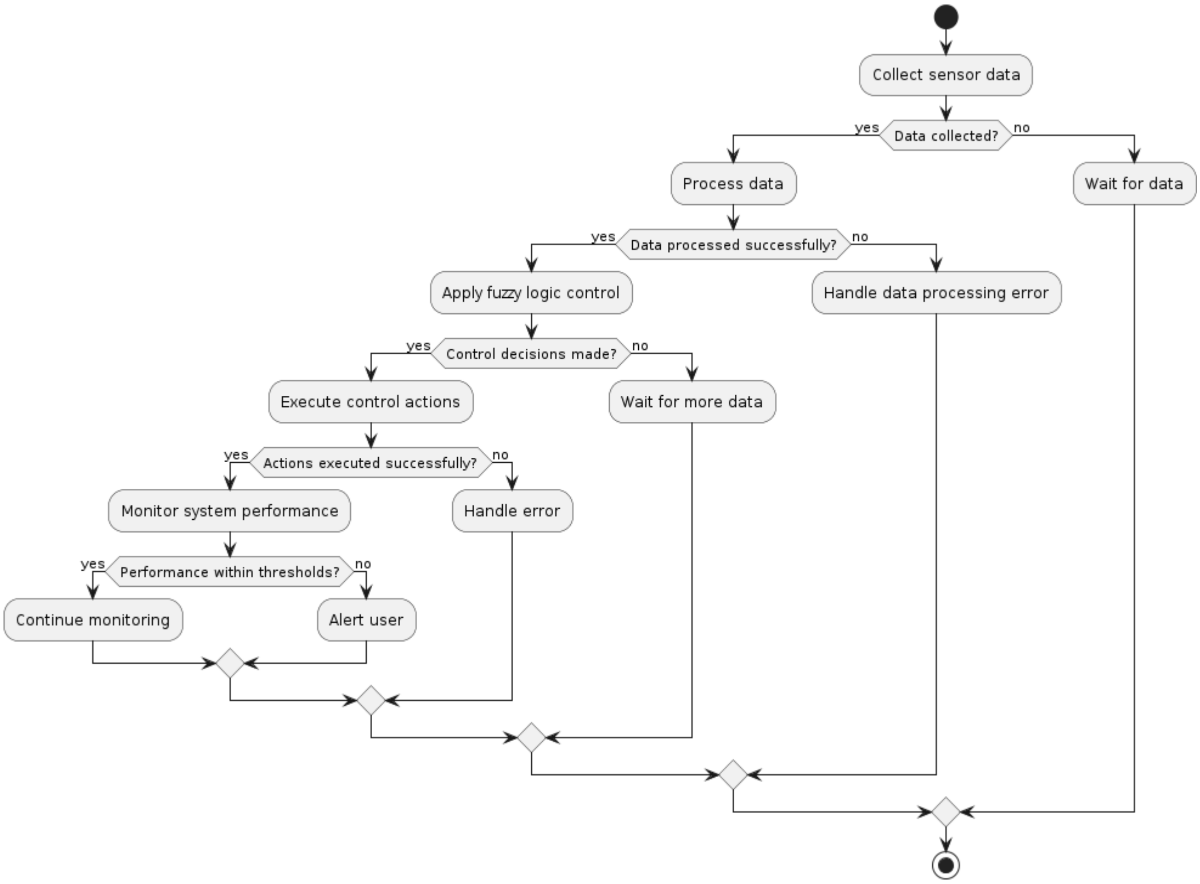

Fig. 1: Working of the proposed system

maintenance, such as using chemicals to protect plants from certain pests. The model system allows the irrigation pump to water plants when it detects readings below the predetermined thresholds. The fuzzy model makes this choice because of the following: According to the standard readings, the plant environment is either too hot or too dry, and if crops are not watered promptly, they may quickly dry out. Growers do not need to be physically present or keep an eye on the soil during this process because the system is automated. With the aid of an automatically operating pump-and-sensor complex, the system thus establishes an ideal condition for watering the plants, giving them precisely the correct amount of water. Similarly, based on the readings, the system can regulate soil fertilization and advise farmers on the ideal concentration of specific nutrients. Hourly sensor readings and corresponding pump responses are detailed in Table 2.

3.2 Fuzzy logic model

The operational flow of the fuzzy logic–based decision-making system is shown in Fig. 2. Using real-time sensor data from the agricultural environment, the fuzzy logic model employed in this study addresses decisions about pest control, nutrient management, and irrigation scheduling. Fig. 2 illustrates how the suggested model operates. The model's linguistic variables, membership functions, fuzzy rules, and inference mechanisms work together to analyze the complex state of the environment and produce pertinent decisions. Linguistic variables that represent the input and output values of the control system are at the heart of the fuzzy logic model. These variables, which are defined as “temperature”, “humidity”, “soil moisture”, “light intensity,” etc., reflect the qualitative aspects of the phenomena under consideration. In addition to the variables themselves, there are linguistic terms that describe the parameters low, medium, high, etc. in relation to the various levels that the sensors in the environment experience.

A membership function that specifies "the degree of membership of a given input value to the variable" in a corresponding linguistic term is also linked to each linguistic variable. The degree of truth of each linguistic term to a variable's input value is described by membership functions, which are shown as triangular, trapezoidal, or Gaussian curves. A membership function for the term "low temperature," for example, would show a high degree of truth value at low temperatures and progressively drop as the temperature rose. The reasoning process that enables the model to make decisions is implemented by fuzzy rules.

The if-then statements that explain the connection between the input values and the control actions are represented by these rules. The expert's knowledge, experimental findings, or other information about the ideal system behaviour are all incorporated into the rules. The fuzzy rule might be, for instance, "increase irrigation frequency if temperature is high and soil moisture is low."

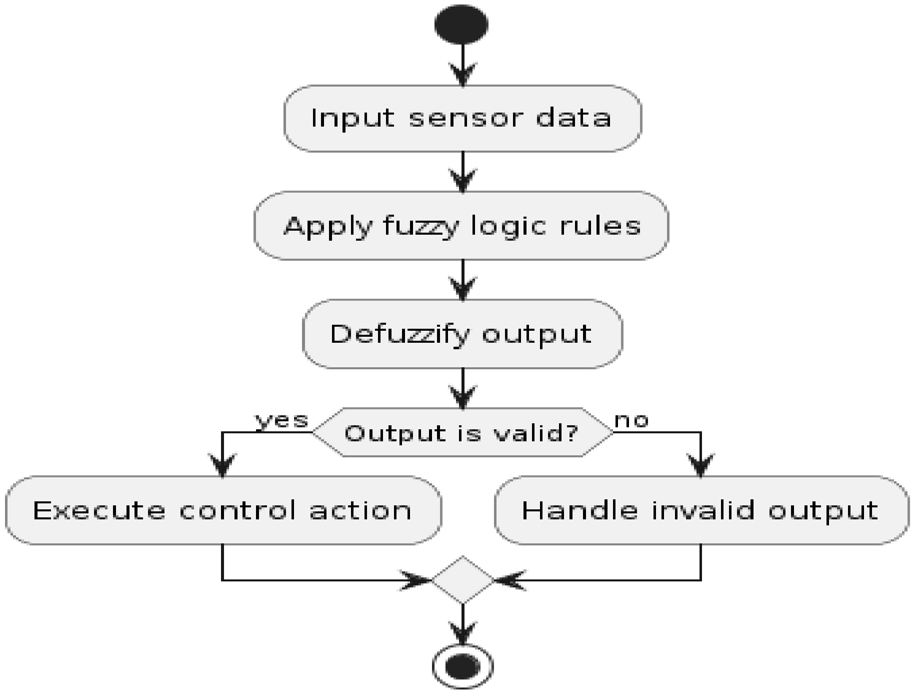

Fig. 2: Working of the fuzzy system

Based on the ideas of fuzzy logic, the fuzzy inference mechanism generates clear output values or recommendations using the fuzzy rules, membership functions, and linguistic variables. Fuzzification and defuzzification are the two stages of the inference process. The first step involves using the proper membership functions associated with each linguistic variable to transform the sharp input values picked up by the sensors into fuzzy sets. Each linguistic term is used to estimate the input values' degree of truth or applicability. The next step involves applying the fuzzified values to the rules. This is done by analysing each rule's antecedents to determine which premise has the greatest degree of application. Following defuzzification, which turns the fuzzy set into a distinct value, the premises and conclusions of the applied rules are then merged into a single fuzzy set. Consequently, the input data from the weather station and sensors is used to generate a recommendation. The historical sensor data that is stored and aggregated in the cloud is used to train the fuzzy logic model.

They are then combined with sensor data to test the model and make improvements over time. To increase the model's decision-making efficiency, the training process focuses on optimizing the fuzzy rules and membership functions. Determining the ideal values for the facility's parameters during training is also crucial. Usually, such optimization is used to carry out this process, methods such as genetic algorithms, gradient descent, and various heuristic optimization techniques. In particular, during the training processes, the weights of the fuzzy rules and the parameters and form of the membership functions are continuously changed.

The validation process can then be used to demonstrate the model's efficacy and validity. This step typically entails evaluating the model on a different validation dataset, though it can also be tested in a simulation experiment with various performance settings. Lastly, based on the current sensor level, the developed and validated model can be used in the agricultural environment to provide real-time recommendations for irrigation, nutrient management, and pest protection.

3.3 Performance score used in research

Several key performance indicators have been employed to assess the effectiveness of the fuzzy logic model of water pump operation and prediction for smart farming. First and foremost, the model's output accuracy was crucial because it indicated how likely it was that the pump would function effectively and dependably in the intended setting. Here, the number of instances of correctly identified times when the plantation requires watering, thus precisely forecasting when the pump should operate, allowed for the determination of the model's prior accuracy. When the plantation is not in need of watering, it is appropriately marked as not requiring activation, which is still a crucial component of operational accuracy.

The assessment of the frequency and duration of the pump's operation, however, demonstrates the operational accuracy of the fluid logic model. The metric also takes into account how well the model can predict when crops will actually need to be irrigated. Therefore, evaluating the model's capacity to prevent crop over- and under-irrigation is just as crucial as evaluating its noted accuracy. The operational performance score in this instance includes a metric that characterizes the fuzzy logic model's capacity to operate the pump during believable irrigation periods while referencing a few evaluation-accepted points of inaccuracy.

A test to ascertain the readiness to work based on the assessment of a change in characteristics or other factors in the test sample is an additional component of the evaluation of the fuzzy logic model related to headphones. The effectiveness of the fuzzy logic model was assessed in this testing environment based on its quality and concentration from all errors. However, the operation's dependability was assessed based on the pump's performance during the designated irrigation periods rather than in many crop-irrigation scenarios.

4. Result and Discussion

A comparative analysis of system performance before and after implementation is presented in Fig. 3. The fuzzy logic model's performance is rigorously tested following implementation. In order to determine the applicability and dependability of this machine learning model, various kinds of Metrics like precision, effectiveness, responsiveness, and dependability are evaluated. Additionally, the algorithm's ability to forecast how a water pump will operate in a smart farming application is evaluated.

Table 1 displays the performance's outcomes. First, accuracy indicates how well the model uses the sensor data to make irrigation decisions. It reaches 96.5%, indicating that the model makes the right irrigation decision 96.5% of the time, demonstrating its high degree of accuracy and ability to determine when irrigation is required. Second, efficiency is a measure of how well the model works to only activate the water pump when necessary. It reaches 95.3%, indicating that the model only activates the pump when necessary and does not waste resources. Third, since it impacts crop care success, the model's responsiveness that is, how quickly it adjusts the water supply in response to changes in the environment is crucial. One minute is the model's response time, which appears to be enough to adapt the irrigation to the changes. Lastly, given the fuzzy logic rules and the various environmental circumstances, it makes sense to talk about the modelled water pump's dependability. The model appears to be dependable and achieves 98.7% pump uptime. In summary, the findings are useful for learning more about the model's ability to preserve the crisp inputs' sensitive values. The results make it possible to determine that the fuzzy model can be defined by its high degree of accuracy, efficiency, responsiveness, and reliability, all of which enable it to have an impact on an agricultural smart farming system.

The quantitative performance evaluation of the proposed fuzzy logic model is summarized in

Table 1.

Table 1: Performance of the Model

Performance Metric	Value
Accuracy	96.5%
Efficiency	95.3%
Responsiveness	Within 1 minute
Reliability	98.7% uptime

Fig. 3 displays the system's effectiveness both before and after it was put into place. Prior to implementation, water usage was 75% effective. This indicates that agriculture made efficient use of 75% of the water resources. At 150 kW per day, the energy consumption was high. This data point showed that a lot of energy was needed for irrigation and other agricultural operations. Lastly, the conveyed level of agricultural management had a low cost-effectiveness of 30%. As a result of the improvements seen in every area, the new system's implementation brought about positive changes. The efficiency of water use rose by 15%, or more than 90%. Since the energy used for irrigating and other agricultural processes became more efficient, the level of energy consumption decreased until it reached 100kW/day. Lastly, cost-effectiveness was over 80%, and this parameter had a notable positive change.

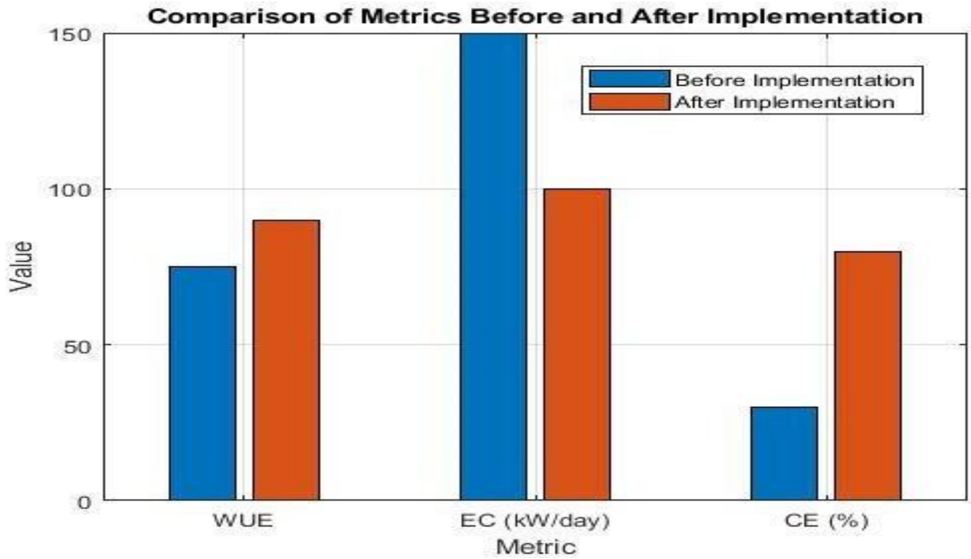

Fig. 3: Before and after implementation of system

The sensor readings and actions of a smart farming system aimed at improving irrigation management are displayed in Table 2 below. Over the course of a day, each parameter is measured hourly. Temperature, humidity, light, and moisture are among the environmental variables that are monitored, so we get information about each of the related elements simultaneously. The parameter that focuses on the reservoir's water level, which is expressed in centimetres, is particularly pertinent. The smart system will use the pump to make sure the plants get the water they need for healthy growth if this level falls below the permitted minimum. However, the pump won't run if the water level is higher than the permissible minimum, allowing for energy conservation and a reduction in water waste. The dynamics of the level as provided by the sensors will therefore have a significant influence on the pump's operation. The action will cause the pump to supply water if the soil's moisture content drops noticeably, as indicated by the corresponding factor in the Table 2. In order to prevent water waste and overuse, the system will activate the pump to deliver water, ensuring that the plants continue to receive the necessary amount of moisture. Hourly sensor readings and corresponding pump responses are detailed in Table 2.

Table 2: Sensor Reading and Response

Time (HH:MM)	Temperature (°C)	Humidity (%)	Soil Moisture (%)	Light Intensity (lux)	Water Level (cm)	Pump Operation
08:00	25	60	40	500	20	Off
09:00	26	58	42	550	18	Off
10:00	28	55	45	600	15	On
11:00	30	52	48	650	12	On
12:00	32	50	50	700	10	On
13:00	33	48	52	750	8	On
14:00	34	47	54	800	6	On
15:00	33	48	53	780	7	On
16:00	32	50	51	760	9	On
17:00	31	52	49	740	11	On
18:00	30	54	47	720	13	On
19:00	28	56	45	700	15	On
20:00	27	58	43	680	17	On

If the performance of the fuzzy logic model and optimal or alternative control strategies were directly compared, it would be evident that the latter consistently performs worse than the former in terms of precision, resource optimization, yield, labour, and risk management. The imposition of a strict structure that doesn't alter the regular operating schedule could be the cause of the former. Because of this, the amount of water, fertilizer, and pesticides used is set at present levels and does not adapt to the needs of various crops or shifts in the real environment. The workload varies as a result, as does the amount of money spent on resources or the use of equipment. Overall, by enabling precise, prompt corrections, the application of the fuzzy logic model would result in increases in these corresponding measures. Farmers would save a great deal of time by using automated systems, which would not only apply the necessary actions at the right times but also lessen the need for manual labour and monitoring. Crucially, the application of the fuzzy logic model aids in risk control by predicting and responding to possible emergencies such as droughts and floods. All things considered, a comparison of the fuzzy logic model with traditional or alternative approaches shows how revolutionary the former can be in transforming agriculture and raising the profitability of these businesses.

5. Conclusion

By creating a smart farming and monitoring system using fuzzy logic system monitoring and controlling, this study sought to increase agricultural yield. Significant environmental factors, including temperature, humidity, soil moisture, light, and water level, were measured using a variety of sensor types. By using a fuzzy logic rule-based system and decision-making technique, this smart farming system shows how irrigation facilities can be used at the right times to improve farming, monitoring, and pest control, ultimately leading to increased agricultural productivity. After analysis and testing, the fuzzy logic sensor's performance appears to be precise and suitable for the water pump motor system with the speed motor's effective operation and prediction. The fuzzy logic system is adaptable to changes in temperature and humidity, makes efficient use of the resources available, and offers chances to boost agricultural productivity and farmer income while centralizing farming. Comparing it to other control techniques and farming-based systems reveals its significance and potential, and the most successful and efficient computerized structure is a smart farming system that uses fuzzy logic. It is recommended that future studies focus on improvements in sensor systems and the use and expansion of creation of cutting-edge IT systems. Improvements in farming systems can be made based on the interdisciplinary aspect, and it may be beneficial to the agricultural sector to enable development. Thus, the significance of artificial intelligence and sensor technology through the use of fuzzy logic technology appears to be recognized, and both contribute to the agricultural sector's prosperity in terms of sustainability and viability from a fresh perspective. The key contribution of this work lies in the practical implementation and performance evaluation of a fuzzy logic–controlled smart farming system under real operating conditions. Experimental results demonstrate high accuracy (96.5%), efficiency (95.3%), rapid responsiveness (within one minute), and strong reliability (98.7% uptime) in automated irrigation control. These results confirm that the proposed approach outperforms conventional methods by reducing water and energy consumption, lowering labor dependency, and enhancing overall agricultural productivity. Consequently, this study highlights the potential of integrating fuzzy logic, IoT, and embedded systems to develop intelligent, sustainable, and scalable solutions for modern agriculture.

References

1. Prathibha, S. R., Hongal, A., & Jyothi, M. P. (2017). IOT based monitoring system in smart agriculture. *Proceedings of the 2017 International Conference on Recent Advances in Electronics and Communication Technology (ICRAECT 2017)*, 81–84. https://doi.org/10.1109/ICRAECT.2017.52
2. Preetha, M., Prabha, R., Deivakani, M., & Tamil Selvi, V. (2023). Efficient re- clustering with novel fuzzy-based grey wolf optimization for hotspot issue mitigation and network lifetime enhancement. *Journal of Ad Hoc & Sensor Wireless Networks, 56*(4), 273–297.
3. Guo, Y., et al. (2020). Plant disease identification based on deep learning algorithm in smart farming. *Discrete Dynamics in Nature and Society, 2020*, 1–10. https://doi.org/10.1155/2020/2479172
4. Dimatira, J. B. U., et al. (2017). Application of fuzzy logic in recognition of tomato fruit maturity

in smart farming. *Proceedings of the IEEE Region 10 Annual International Conference (TENCON)*, 2031–2035. https://doi.org/10.1109/TENCON.2016.7848382
5. Srinivasan, S., Deva Hema, D., Singaram, B., Praveena, D., Kishore Mohan, K. B., & Preetha, M. (2024). Decision support system based on Industry 5.0 in artificial intelligence. *International Journal of Intelligent Systems and Applications in Engineering, 12*(15s), 172–178.
6. Devikala, S., Rabi, J., Murugan, V. P., Christy Mano Raj, J. S., Mohanasundaram, K., & Sivakumar, K. (2024). Development of fuzzy logic controller in automatic vehicle navigation using IoT. *Journal of Electrical Systems, 20*(3s), 114–121. https://doi.org/10.52783/jes.1254
7. Paraforos, D. S., et al. (2022). Connecting agricultural robots and smart implements by using ISO 11783 communication. *IFAC-PapersOnLine, 62*(2), 123–133. https://doi.org/10.1016/j.ifacol.2022.11.139
8. Akbar, M. O., et al. (2020). IoT for development of smart dairy farming. *Journal of Food Quality, 2020*, 1–10. https://doi.org/10.1155/2020/4242805
9. Srinivasan, S., Sajini, S., Singaram, B., Saravanan, K., & Kishore Mohan, K. B. (2024). Deep graph neural networks for multi-image super resolution reconstruction. *International Journal of Intelligent Systems and Applications in Engineering, 12*(15s), 158–164.
10. Ferehan, N., Haqiq, A., & Ahmad, M. W. (2022). Smart farming system based on intelligent Internet of Things and predictive analytics. *Journal of Food Quality, 2022*, 1–10. https://doi.org/10.1155/2022/7484088
11. [Rakhra, M., Sanober, S., Quadri, N. N., Verma, N., Ray, S., & Asenso, E. (2022). Implementing machine learning for smart farming to forecast farmers' interest in hiring equipment. *Journal of Food Quality, 2022*, 1–10. https://doi.org/10.1155/2022/4721547
12. [Raghuvanshi, A., et al. (2022). Intrusion detection using machine learning for risk mitigation in IoT-enabled smart irrigation in smart farming. *Journal of Food Quality, 2022*, 1–10. https://doi.org/10.1155/2022/3955514
13. Sivakumar, K., Balamurali, D., Kathiresh, P. V. M., & Damodaran, S. (2018). Design and optimization of spur gearbox parameters. *International Research Journal of Automotive Technology (IRJAT), 1*(4), 34–40.
14. Phasinam, K., Kassanuk, T., & Shabaz, M. (2022). Applicability of Internet of Things in smart farming. *Journal of Food Quality, 2022*, 1–10. https://doi.org/10.1155/2022/7692922
15. Kim, S., Lee, M., & Shin, C. (2018). IoT-based strawberry disease prediction system for smart farming. *Sensors, 18*(11), 4051. https://doi.org/10.3390/s18114051
16. Ather, D., et al. (2022). Selection of smart manure composition for smart farming using artificial intelligence technique. *Journal of Food Quality, 2022*, 1–10. https://doi.org/10.1155/2022/4351825
17. Arun Prakash, V. R., et al. (2020). Mechanical, thermal and fatigue behaviour of surface-treated novel *Caryota urens* fiber–reinforced epoxy composite. *Biomass Conversion and Biorefinery*. https://doi.org/10.1007/s13399-020-00938-0
18. Lal, P. P., et al. (2022). IoT integrated fuzzy classification analysis for detecting adulterants in cow milk. *Sensing and Bio-Sensing Research, 36*, 100486. https://doi.org/10.1016/j.sbsr.2022.100486
19. Shukla, R., Vishwakarma, N. K., Mishra, A. R., & Mishra, R. (2022). Internet of Thingsapplication: E-health data acquisition system and smart agriculture. *Proceedings of the International Conference on Emerging Trends in Engineering and Technology (ICETET 2022)*, 12–16. https://doi.org/10.1109/ICETET-SIP- 2254415.2022.9791834

20. Verdouw, C., Sundmaeker, H., Tekinerdogan, B., Conzon, D., & Montanaro, T.(2019).Architecture framework of IoT-based food and farm systems: A multiple case study. *Computers and Electronics in Agriculture, 165*, 104939. https://doi.org/10.1016/j.compag.2019.104939
21. Sivakumar, K., Sathiyamoorthy, V., Balamurugan, S., Palani, S., Sivakumar, A., & Anbazhagan, R. (2021). Experimental investigation of process parameter influences of electrochemical micro machining process on Al metal matrix composite. *Journal of Huazhong University of Science and Technology, 50*(3), 50–56.
22. Mohammed Thaha, M., Preetha, M., Sivakumar, K., & Ramadass, R. (2023). An aerial robotics investigation into the stability, coordination, and movement of strategies for directing swarm and formation of autonomous MAVs and diverse groups of driverless vehicles (UGVs). *International Journal on Recent and Innovation Trends in Computing and Communication (IJRITCC), 11*(3), 301–304.
23. Veena, S., Ramyadevi, K., Elavarasi, K., & Preetha, M. (2019). Smart car automated system to assist the driver in detecting the problem and providing the solution. *International Journal of Innovative Technology and Exploring Engineering (IJITEE), 8*(6S4), 267–271.
24. [Ariunaa, K., Tudevdagva, U., & Hussai, M. (2022). FPGA-based digital filter design for faster operations. *Journal of VLSI Circuits and Systems, 5*(2), 56–62. https://doi.org/10.31838/jvcs/05.02.09
25. Preetha, M., Elavarasi, K., Mani, A., Pavithra, E., Sudharshna, P., & Rakshini, S. (2021). A survey on decentralized crowdsourcing using blockchain technology. *Further Advances in Internet of Things in Biomedical and Cyber Physical Systems, 4*(12), 373–382. https://doi.org/10.1007/978-3-030-57835-0_27
26. Chamara, N., Islam, M. D., Bai, G. (Frank), Shi, Y., & Ge, Y. (2022). Ag-IoT for crop andenvironment monitoring: Past, present, and future. *Agricultural Systems, 203*, 103497.https://doi.org/10.1016/j.agsy.2022.103497
27. Ahmad, I., Abdullah, S., & Ahmed, A. (2022). IoT-fog-based healthcare 4.0 system using blockchain technology. *Journal of Supercomputing, 79*(4), 3999–4020. https://doi.org/10.1007/s11227-022-04788-7
28. Sinha, M. K., & Tiwari, R. K. (2024a) “Utilizing fuzzy logic in precision agriculture Techniques for disease detection and management” *Journal of Statistics and Mathematical Engineering, 10*(1), 35–40. https://doi.org/10.46610/JOSME.2024.v10i01.005
29. Sinha, M. K., & Tiwari, R. K. (2024b), “A comprehensive survey of fuzzy logic utilization in different agricultural sectors” *Journal of Statistics and Mathematical Engineering, 10*(1), 1–7. https://doi.org/10.46610/JOSME.2024.v10i01.001
30. Sinha, M. K., & Tiwari, R. K. (2024c), “Application of adaptive neuro-fuzzy inference system (ANFIS) for optimizing nano-biochar application in soil remediation projects in Chas” *Communications in Mathematics and Applications, 15*(5), 1443–1457. https://doi.org/10.26713/cma.v15i5.2903