Intelligent IoT-Based Data Analytics System for Precision Farming Using Regression Techniques

Anidi Anidi[1], Arna Juwariyah[2], Ahmed Aljuboori[3] and Shahad Lateef Abdulwahid[4]
[1]*Department of Early Childhood Education, Universitas Sulawesi Tenggara, 93121 Kendari, Indonesia*
[2]*Department of Premary Teacher Education, Universitas Sulawesi Tenggara, 93121 Kendari, Indonesia*
[3]*Department of Computer Science, Dijlah University College, 10021 Baghdad, Iraq*
[4]*Faculty of Computer Engineering, Imam Ja'afar Al-Sadiq University, 62001, Maysan, Iraq*
anidi@un-sultra.ac.id, arnajuwariyah@un-sultra.ac.id, a.s.aljuboori@duc.edu.iq, Shahadlateef17@gmail.com

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Abstract: Increasing global demands for sustainable agricultural practices, triggered by food security and climate change, have evolved precision farming. By combining machine learning with the Internet of Things (IoT), precision agriculture can optimize resource use and crop yields. Data analytics based on IoT are used here to enhance agricultural decision-making by using regression techniques like Support Vector Machines (SVMs) and Multilayer Perceptrons (MLPs). Data from environmental and soil sensors are collected in agricultural fields, including temperature, humidity, nitrogen, phosphorus, potassium, pH, and rainfall. Utilizing machine learning algorithms, this data is processed to predict which crops will yield the highest yields and utilize the most resources. Based on a comparative analysis, MLP models exhibit superior performance to SVM models with respect to training time, testing time, and regression error (lower RMSE). It achieves the highest classification accuracy (92%) among existing models such as SPS, CSMS, and SRIM. When farmers have access to real-time, data-driven insights, they can make better decisions, increase productivity, and adopt more sustainable farming practices.

1 INTRODUCTION

The Internet of Things (IoT) has revolutionized many industries, including agriculture, thanks to its rapid growth. The concept of precision farming, which maximizes agricultural practices based on real-time data, has emerged as a powerful way to enhance productivity, resource management, and sustainability. IoT-based data analytics systems play an important role in this sector due to the collection and analysis of sensor and device data on the ground [1]. By making informed decisions, farmers are able to increase yields and reduce costs by irrigating, fertilizing, controlling pests, and harvesting effectively. In agricultural data analysis, regression techniques are particularly valuable. Based on historical and real-time inputs, they help predict key variables such as soil moisture levels and crop growth rates. The integration of IoT devices with intelligent regression models enables highly accurate forecasting systems to be developed, which can adjust to dynamic environmental conditions and optimize farm management. It is designed to provide farmers with a robust tool to enhance decision-making processes by bridging the gap between data collection and actionable insights. This study aims to harness the application of advanced analytics to agricultural IoT data in order to promote environmental conservation, ensure food security, and develop sustainable agricultural practices as a result of global challenges such as climate change and population growth.

With precision farming, modern agriculture is becoming more productive, efficient, and sustainable. With the growing demand for food and the challenges posed by climate change, agriculture practices must be optimized. Many benefits can be achieved by analyzing data using IoT and machine learning. Real-time monitoring of environmental conditions, soil quality, crop health, and other critical parameters is made possible by the Internet of Things. To provide actionable insights, these devices require massive amounts of data to be processed intelligently. A regression algorithm is a powerful tool for analyzing and predicting agricultural outcomes, including yield estimates, irrigation requirements, and pest management measures. Agrarian practices have become outdated due to a shortage of supplies, incompetence with technology, and a lack of knowledge among farmers [2], [3]. It is also common for pests and insects to reduce the yield of certain crops. Pests and insects have attacked several crops. Animals and birds can be poisoned by some insects and pesticides, making them ineffective. Additionally, it damages animal and food chains' natural food webs [4]. Due to crop diseases, there is a significant reduction in throughput. Approximately 40% of agricultural yield loss occurs due to insects, pests, viruses, animals, and weeds, according to [5]. Pests, diseases, animals, and weeds are responsible for 40% of agricultural yield losses, according to [5]. Moreover, they have both short- and long-term effects, some of which are temporary and others are permanent [6]. A lot depends on the weather when it comes to agriculture. The weather has a significant impact on agriculture.

We live in a world where technology is everywhere. Currently, remote monitoring techniques are used to provide relevant information to farmers [7]. Several factors contribute to this, including WiFi sensor networks and the Internet of Things [1]. Miniaturization led to the development of the Internet of Things [8]. During his 1999 lecture on Supply Chain Management, Kevin Ashton mentioned the Internet of Things for the first time [9]. In the Internet of Things, a sensor can uniquely identify a smart object. Any object, sensor, person, or smart device that connects and shares information is considered a "thing" [10]. The traditional method of detecting diseases and pests by hand and calculating quantity and production based on statistics resulted in human error in the past [11], [12]. The technology learns from its experiences through machine learning. By analyzing and modelling large datasets collected from crop fields, valuable insights can be gained. This technique identifies hidden patterns in horticulture, including salt content, temperature, and humidity. Several machine-learning approaches can be used for crop disease prediction, such as artificial neural networks, SVM regressions, logistic regressions, fuzzy technologies, etc [13]. [14]. The use of machine learning to predict apple diseases has been developed by scientists. Additional information about coronaries can be derived from apple leaf images in addition to apple scab images. Four algorithms were used to classify the same dataset: Support Vector Machine, K Nearest Neighbor, Decision Tree, and Naive Bayes [13]. Matlab 2016 was used for simulations. According to this study, KNN categorizes diseases with 99.4% accuracy. Himachal Pradesh and Uttarakhand developed it as an alternative to existing systems that were unreliable and expensive. Predicting crop diseases using IoT and machine learning was discussed during the presentation [15]. The system's model was developed by combining IoT and machine learning. Several environmental sensors collected data, including a temperature sensor and a humidity sensor.

2 LITERATURE REVIEW

In the soil, plants can find the nutrients they need to thrive. Minerals in the soil are necessary for growth, but if any are missing, the plant will have trouble growing. Soil composition must be regularly tested to ensure that plants receive enough nutrients. An application of fertilizer high in nutrients may correct nutrient deficiency problems in the soil. Fertilizers have positively influenced agricultural output, but their extensive use has caused ecological damage. The importance of soil nutrient testing in agriculture can be attributed to this fact. Even though conventional soil testing provides accurate data, it is unsuitable for precision agriculture because of the cost and time involved in obtaining the results. Tests that test a larger number of samples are prohibitively expensive, so they cannot measure a field's geographic heterogeneity. Therefore, fast, portable, economical, and highly precise methods are essential for achieving the best results [16].

An expanding population and careful management are essential for agriculture. According to the authors [17], the modern agricultural system relies heavily on human labour but is highly mechanized. The return on a thirty per cent investment from 1920 to 1970 was one hundred eighty per cent. A significant increase in productivity was not the result of a rise in data sources but rather of advances in farming techniques. It has been found that sifting machines, mechanical innovations, and synthetic manures contribute to agricultural profitability. Technology has become more important to farmers over the last decade for communicating and storing information. They can, therefore, better monitor their financial data and interactions with third parties. We live in a world where information is readily available. As a result, farmers can easily collect data and conduct statistical analyses using field observations in horticulture.

According to the authors [18], several proprietary techniques can be used to improve agricultural monitoring. When it comes to keeping track of geographical regions and climatic punctuations, researchers have found more complex frameworks. Over time, Farm Management Information Systems

(FMIS) have evolved to address the specific needs and activities of farms. In the present day, these frameworks are integrating into the Internet age by utilizing established systems management and responses to strengthen agricultural structures. As time has progressed, Farm Management Information Systems, or FMIS, have evolved to meet the specific needs of farms. However, many people think the Internet is not perfect, particularly when it comes to managing a large number of connected devices, such as IoT devices or stakeholder devices. There is, however, no standardized solution that can ensure reliable interoperability between relevant authorities. FI has been providing frameworks to help close these gaps since that time.

In recent years, farmers have been urged to adopt thorough management practices, and a sensor-based approach could finally allow them to do so. It has been demonstrated that sensors play an important role in agriculture, and their fundamental role has been defined. To measure farming efficiency, the Precision Agriculture Monitor System (PAMS) uses Shining sensors. A monitoring and regulation system such as the IFarm Framework is recommended to increase agricultural production by reinforcing socioeconomic elements. Monitoring and regulating water usage may be easier with this system. Using a variety of characteristics, [19], [20] classified sensor technologies according to their performance.

The media, government agencies, and farm-based equipment are the main sources of precision agricultural information in Texas and New Mexico, two states that grow cotton [21]. Precision agriculture technology can be influenced in various ways by data from a variety of sources. GPS-enabled yield monitors and soil survey maps are popular examples. Dealers contribute to the implementation of zone soil sampling and soil survey maps in varying degrees. Smart farming relies heavily on ML and the IoT. When implementing these practices, farmers face several challenges, including predicting crop diseases. Several diseases affect apple crops, but apple scab is the most common. Using WSNs [22], [23] in apple orchards allows real-time data collection and early disease prediction. Additionally, he discussed the challenges farmers face when handling hardware units and sensors due to environmental factors [24]. As part of precision farming, automated devices, Internet of Things sensors, real-time data collection, and cloud storage are used, as well as data analysis. Irrigation systems and greenhouses can be controlled smartly using a framework proposed by one author. Nutritional, climate, and irrigation data can be stored, managed, and analyzed with it [25]. Because the soil nutrition level decreases from year to year due to cultivation, this method maximizes soil fertility [26]. Combined with IoT sensors and smart tools, big data plays an increasingly important role. An article addressed the volume of sensor data generated, cloud storage availability, and challenges associated with real-time data analysis and visualization [27].

It was proposed that WSNs and IoTs be used for precision agriculture and irrigation monitoring. The implementation and maintenance costs of fully sensor-based agriculture, as well as farmers' lack of knowledge, have been noted as limitations. A farmer could, therefore, make an appropriate decision based on updated information. According to one author, soil samples could be used to predict the type of crop that would be suitable for a particular field. ESP8266 WiFi module, Arduino board, and other sensors were used to collect soil temperatures, moisture, and mineral values. The algorithms that performed most accurately on the rainfall dataset were naive Bayes, logistic, and C 4.5 [28].

3 METHODOLOGY

Agricultural producers have benefited from the Internet of Things by improving irrigation efficiency, increasing yields, and reducing costs. Through the integration of agriculture and information technology, an intelligent agricultural solution can be created. With the advent of IoT technology, three aspects have emerged.

- For years, WSNs have been driving the growth of precision agriculture by enhancing crop yields through the use of advanced technology.
- Crops are currently produced using farming facilities that yield high-quality yields. Inputs are high, outputs are high, capital is high, and labour is high in the production process.
- Producing and managing crops on a contract basis is a relatively new concept in agriculture. Globally, urbanization has outpaced rural development, creating a growing gap between the two. According to statistics, 80% of extremely poor people live in rural areas, and 75% of moderately poor people live in rural areas.

3.1 IoT Framework for Agriculture

Cloud database management systems will access real-world data to train machine learning models using real-world data, which is accessed through storage media. Figure 2 illustrates one of 22 crops that could be implemented as a result of the module.

3.1.1 Data Mining and Network Implementation

A first-level architecture enables utilities to capture and communicate data. Gateways and base stations are connected to the sensor network. The second level incorporates classification algorithms and specifications. Next, the machine learning algorithms must be implemented to acquire the server's results. Irrigation crops are obtained from the server using a trained module. Specific sensors measure temperature, humidity, and rainfall, whereas nitrogen, phosphorus, potassium, and pH parameters are measured by analytical sensors. A spreadsheet was used to compile the data, with 22 different crops as the ground truth. Using machine learning algorithms, the module is trained to recommend crops for irrigation based on the model attained. In the article, it demonstrates how IoT-based smart agriculture can be integrated into the field by combining physical structure, data collection, data processing, and data analytics. From Kaggle, we acquired the datasheet [29]. The crop is irrigated as recommended to predict crop yields and obtain maximum yields.

A variety of environmental factors determine how well crops will be irrigated, such as soil fertility, i.e., nitrogen, phosphorous, and moisture. By considering the 7 attributes, a crop can be irrigated to maximize yield. Based on this article, it can be used to make better decisions about planting different crops. With WEKA or Waikato Environment for Knowledge Analysis, a free, open-source software program licensed under the GNU public license, you can perform a wide range of fact-mining tasks as shown in Figure 1.

3.2 Agriculture Sensor Layer

Mobile devices (smartphones, sensor nodes, etc.) use GPS to create various IoT devices for smart agriculture, such as field sensors, greenhouse sensors, photovoltaic farms, solar insecticide lamps, etc. Consequently, IoT devices can be integrated and adapted to serve two purposes in agriculture. Our first commitment is to provide nutrient solutions in a trustworthy manner, as well as distributing them in a timely manner. As well as improving consumption management, lowering costs, and reducing losses, we strive for a better solution. In addition to being beneficial for the economy, it will also be beneficial for the environment. SCADA systems (supervisory control and data acquisition) are used in agriculture to control operations. IoT sensors and meters are proposed for greenhouses:

IoT sensors and meters are proposed for greenhouses:

- Calculate the water pumping system pressure, drip rate, and surface to be irrigated using IoT devices.
- Water meters that display real-time information display the status of water storage.
- Systems that use IoT to filter water based on physical properties (e.g., sand filters).
- Fertiliser meters should be able to provide real-time updates for injections and storage tanks of NPK fertilisers.
- It is possible to control the pH and electrical conductivity of nutrient solutions through the Internet of Things.

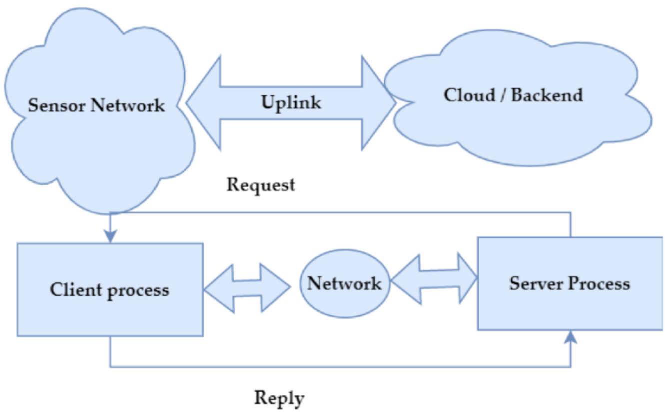

Figure 1: A proposed IoT client-server architecture.

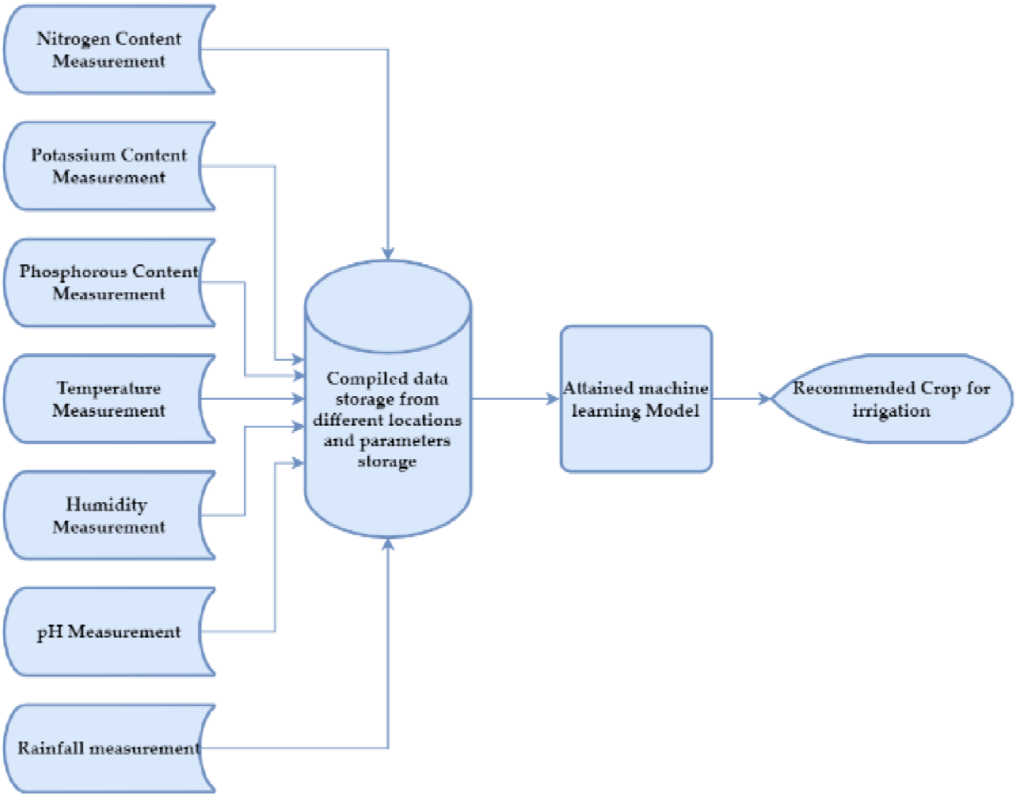

Figure 2: Using machine learning modules to construct a block diagram.

3.3 Fog Computing Layer

Analyzing and making informed decisions is enabled by the analytics and decision-making model, which provides farmers with reports that accompany their decisions. Several states, as well as machine intelligence, are predicted to be created as a result of the in-charge order. On the fog layer of data analytics systems, machine learning algorithms and classification models are typically used.

Sensors initially generate data, which is then acquired by edge devices. A preprocessing step cleans and corrects stored data. Data designed for a particular purpose is used to train machine learning algorithms, which are then initialized to reflect that purpose. A sensor collects data in the Internet of Things, which may be collected in real-time or in batches (for instance, when to pump water) (for example, temperature and humidity). A multilayer perceptron neural network (MLP-ANN) makes predictions and displays data in graphs using support vector machines. In addition to its ability to learn nonlinear models in high-dimensional spaces, this algorithm offers several advantages.

3.3.1 Multilayer Perceptron

This type of NN can also supplement feedforward neural networks. There are three layers in the MLP: input, hidden, and output. As opposed to linear functions, MLP approximates continuous functions. Perceptions, or neurons, are part of the MLP. In this case, $(x = x_1 + x_2 + x_4 + x_5 \dots \dots .. x_n)$ receives n features [30] as input $(x = x_1 + x_2 + x_4 + x_5 \dots \dots .. x_n)$.

Weighted sums are calculated for input layers based on the n features sent to u.

$$u_x = \sum_{i=1}^{n} w_i x_i. \tag{1}$$

A result of this type should be passed on to the activation function [f]. In this article, sigmoid nodes 0 to 35 are supposed to be passed on. A hidden layer or layers can be found in MLP. There is, however, an external layer between the input and output layers.

As far as support vector machines (SVMs) are concerned, they are divided into two categories: classification and regression. The goal of SVM is to shift nonlinear data into a linear space where it can be separated. Two conditions must be met for the hyperplane to effectively separate data: the distance between vectors and the hyperplane must be adapted to differing aspects of the vectors. Here is what the assumption function looks like:

$$f(x_i) = \begin{Bmatrix} +1 \; if \; w.x + b \geq 0 \\ -1 \; if \; w.x + b < 0 \end{Bmatrix}. \qquad (2)$$

Class +1 place points cannot be found above, below, or on the hyperplane, while class-1 place points can be found above, below, and on the hyperplane.

Perceptrons with multiple layers in an artificial neural network (ANN) are called multilayer perceptrons. The animate nervous system is controlled by perceptrons, which are interconnected systems. A deep learning neural network simulates nonlinear functions of high order as its foundation. Here are the steps for calculating the degree of accuracy in output node j based on the above example:

$$e_j(n) = d_j(n) - y_j(n). \qquad (3)$$

Perceptrons produce output values based on goal values. Weight adjustments can reduce the output error by adjusting the nodes' weights.

$$e(n) = \frac{1}{2}\sum_j e_j^2(n). \qquad (4)$$

3.4 Edge Network Layer

Sensors are detected and connected to low-power microcontrollers at remote locations using IoT microcontrollers designed for IoT. Sensor data can be collected, analyzed, and transmitted to the edge layer's base station using the ESP 32 Node MCU. The calibration and comparison of sensors are required for analogue and digital data collection. A healthy and unhealthy climate is collected in order to ensure crop survival.

A climate-based model tracks Gerbera and Broccoli. The parameters of greenhouses are monitored using Node MCU ESP 32 microcontrollers. The data collected by personal computers is serialized with timestamps. A DHT11 sensor measures temperature and humidity, an LDR sensor measures light intensity, an MQ2 sensor measures CO2, and a Cu lead measures soil moisture. Ten days are monitored continuously using the MQTT protocol by Adafruit IO over the cloud platform using a specific time interval. Computers monitor sensor data in real time using cloud-based controllers.

3.5 Cloud Computing Layer

Through an application that uses data from edge layer nodes to process and control at the base station, farmers can monitor crop cultivation progress. The Adafruit IO platform displays, acts on, and interacts with sensor data. Additionally, MQTT ensures that the dossier remains private and secure. The MQTT protocol is an inconsequential problem-solving protocol that is located on TCP/IP. A message broker routes messages through MQTT, connecting senders and receivers that send and receive messages. Publishing and subscribing to messages can be done with the same client. Data is sent from temperature sensors based on a specific subject, such as in a greenhouse system.

4 RESULTS AND DISCUSSION

In Figure 3, the training and testing times for SVM and MLP models are compared. The MLP takes about 450 seconds to train (about 320 seconds), while the SVM takes about 70 to 80 seconds to test. During training, MLP uses more computation than SVM, but during testing, it is similar to SVM.

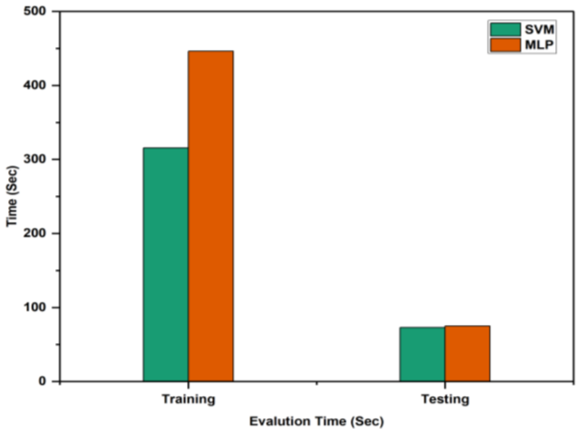

Figure 3: Representation of evaluation time.

A comparison of the SVM and MLP models is presented in Figure 4. Pump and Fan data show that SVM is more accurate than MLP in the Pump and Fan category. Compared to SVM, MLP performs significantly better in the Lift category. Pump and fan performance are better with SVM, whereas lift performance is better with MLP, as shown in Figure 4.

This bar chart compares pumps, fans, and lifts using SVM and MLP models. Pump and Fan performance is slightly better with SVM, while Lift performance is significantly better with MLP. Pump and fan performance are better with SVM, whereas lift performance is better with MLP.

A bar chart representing the average RMSE (Root Mean Square Error) for regression tasks for SVMs and MLPs is shown in Figure 6. MLP is represented by the blue bar, while SVM is represented by the yellow bar. Based on the chart, MLP is better at regression with lower prediction error than SVM (around 0.08), which indicates better regression performance with MLP.

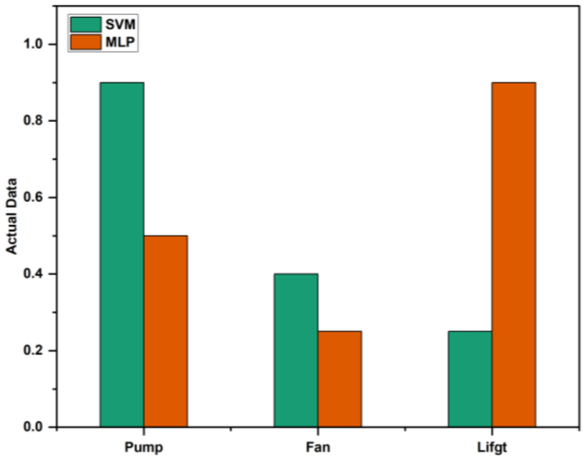

Figure 4: Comparison of SVM and MLP performance across equipment categories.

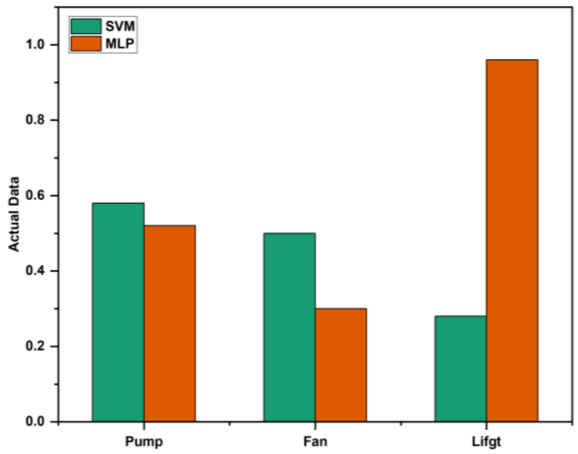

Figure 5: Performance Comparison of SVM and MLP across different equipment types.

In Figure 7, four models are compared, each of which has an accuracy of 92%: the Proposed Model (92%), the SPS (90%), the CSMS (66%), and the SRIM (89%). According to the chart, SRIM and SPS achieve a higher degree of accuracy than the Proposed Model, while CSMS achieves the lowest degree of accuracy. Classification accuracy is better with the Proposed Model than with the other models.

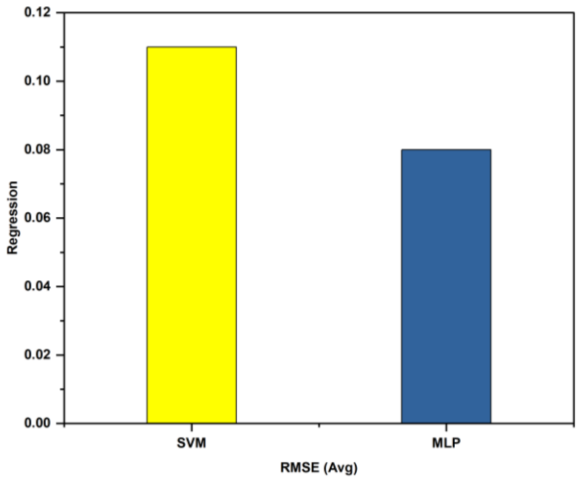

Figure 6: Comparison of average RMSE between SVM and MLP models.

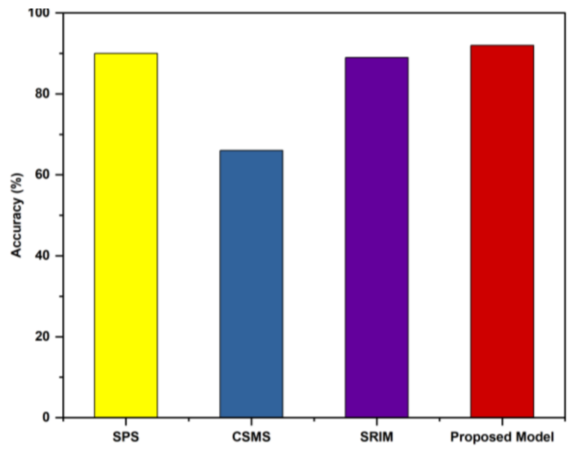

Figure 7: Accuracy comparison of SPS, CSMS, SRIM, and proposed model.

5 CONCLUSIONS

Precision agriculture was the focus of this paper, which presented a data analytics system based on IoT that is intelligent and IoT-based. Real-time data collection, analysis, and actionable insights are delivered through the use of IoT sensors and machine-learning regression models. Training and testing experiments have consistently shown that Multi-Layer Perceptrons (MLPs) outperform Support Vector Machines (SVMs) in terms of Root Mean Square

Error (RMSE) and accuracy metrics. A comprehensive dataset obtained from Kaggle, comprising detailed soil fertility indicators and varied climatic conditions, was employed to rigorously test and validate the effectiveness of the proposed system. The model accurately recommended suitable crops tailored to specific environmental conditions, demonstrating practical applicability. Furthermore, the proposed approach achieved the highest accuracy of 92% when compared with other advanced frameworks such as SPS, CSMS, and SRIM. These results validate that intelligent IoT-based agricultural systems are not only feasible but essential for achieving long-term sustainability and food security. By providing farmers with actionable predictive insights, this technology reduces reliance on traditional, less-efficient agricultural practices, optimizes resource allocation, minimizes environmental impact, and significantly enhances the resilience, productivity, and overall efficiency of modern farming systems.

REFERENCES

[1] B. Bhola et al., "Quality-enabled decentralized dynamic IoT platform with scalable resources integration," IET Communications, p. cmu2.12514, Oct. 2022, doi: 10.1049/cmu2.12514.

[2] K. Bhargava, A. Kashyap, and T. A. Gonsalves, "Wireless sensor network based advisory system for Apple Scab prevention," in Proc. 2014 Twentieth National Conference on Communications (NCC), IEEE, 2014, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/6811263/.

[3] A. Singh et al., "Smart Traffic Monitoring Through Real-Time Moving Vehicle Detection Using Deep Learning via Aerial Images for Consumer Application," IEEE Transactions on Consumer Electronics, vol. 70, no. 4, pp. 7302–7309, Nov. 2024, doi: 10.1109/TCE.2024.3445728.

[4] S. S. Shinde and M. Kulkarni, "Review Paper on Prediction of Crop Disease Using IoT and Machine Learning," in Proc. 2017 Int. Conf. Transforming Engineering Education (ICTEE), Pune: IEEE, Dec. 2017, pp. 1–4, doi: 10.1109/ICTEED.2017.8586207.

[5] E.-C. Oerke, "Crop losses to pests," Journal of Agricultural Science, vol. 144, no. 1, pp. 31–43, 2006.

[6] S. Savary, A. Ficke, J.-N. Aubertot, and C. Hollier, "Crop losses due to diseases and their implications for global food production losses and food security," Food Security, vol. 4, no. 4, pp. 519–537, Dec. 2012, doi: 10.1007/s12571-012-0200-5.

[7] P. Rani, S. P. Yadav, P. N. Singh, and M. Almusawi, "Real-World Case Studies: Transforming Mental Healthcare With Natural Language Processing," in Demystifying the Role of Natural Language Processing (NLP) in Mental Health, A. Mishra, S. P. Yadav, M. Kumar, S. M. Biju, and G. C. Deka, Eds., IGI Global, 2025, pp. 303–324, doi: 10.4018/979-8-3693-4203-9.ch016.

[8] R. Buyya and A. V. Dastjerdi, Internet of Things: Principles and Paradigms, Elsevier, 2016. [Online]. Available: https://books.google.com/books?hl=en&lr=&id=_k11CwAAQBAJ.

[9] K. Ashton, "That 'internet of things' thing," RFID Journal, vol. 22, no. 7, pp. 97–114, 2009.

[10] P. Rani et al., "An Implementation of Modified Blowfish Technique with Honey Bee Behavior Optimization for Load Balancing in Cloud System Environment," Wireless Communications and Mobile Computing, vol. 2022, pp. 1–14, May 2022, doi: 10.1155/2022/3365392.

[11] T. Rumpf et al., "Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance," Computers and Electronics in Agriculture, vol. 74, no. 1, pp. 91–99, 2010.

[12] P. Rani et al., "Simulation of the lightweight blockchain technique based on privacy and security for healthcare data for the cloud system," International Journal of E-Health and Medical Communications (IJEHMC), vol. 13, no. 4, pp. 1–15, 2022.

[13] P. Rani and R. Sharma, "Intelligent transportation system for internet of vehicles based vehicular networks for smart cities," Computers & Electrical Engineering, vol. 105, p. 108543, 2023.

[14] S. Singh and S. Gupta, "Digital image processing techniques for early detection and classification of different diseased plants," International Journal of Bio-Science and Bio-Technology, vol. 8, no. 4, pp. 61–66, 2016.

[15] G. Ansari, P. Rani, and V. Kumar, "A Novel Technique of Mixed Gas Identification Based on the Group Method of Data Handling (GMDH) on Time-Dependent MOX Gas Sensor Data," in Proc. Int. Conf. Recent Trends in Computing, vol. 600, Springer Nature Singapore, 2023, pp. 641–654, doi: 10.1007/978-981-19-8825-7_55.

[16] P. Rani et al., "Deep Learning and AI in Behavioral Analysis for Revolutionizing Mental Healthcare," in Demystifying the Role of Natural Language Processing (NLP) in Mental Health, A. Mishra et al., Eds., IGI Global, 2025, pp. 263–282, doi: 10.4018/979-8-3693-4203-9.ch014.

[17] A. L. Olmstead and P. W. Rhode, "Conceptual issues for the comparative study of agricultural development," in Agriculture and Economic Development in Europe since 1870, Routledge, 2008, pp. 47–71. [Online]. Available: https://www.taylorfrancis.com/chapters/edit/10.4324/9780203928776-9.

[18] M. A. Alqahtani, "Machine learning techniques for malware detection with challenges and future directions," International Journal of Communication Networks and Information Security, vol. 13, no. 2, pp. 258–270, 2021.

[19] M. H. Anisi, G. Abdul-Salaam, and A. H. Abdullah, "A survey of wireless sensor network approaches and their energy consumption for monitoring farm fields in precision agriculture," Precision Agriculture, vol. 16, no. 2, pp. 216–238, Apr. 2015, doi: 10.1007/s11119-014-9371-8.

[20] P. Rani and M. H. Falaah, "Real-Time Congestion Control and Load Optimization in Cloud-MANETs Using Predictive Algorithms," NJF Intelligent Engineering Journal, vol. 1, no. 1, pp. 66–76, 2024.

[21] M. Csótó, "Information flow in agriculture–through new channels for improved effectiveness," Journal of Agricultural Informatics, vol. 1, no. 2, 2010. [Online]. Available: http://magisz.org/journal/index.php/jai/article/view/17

[22] N. Kumar et al., "Teeech: Three-tier extended energy efficient clustering hierarchy protocol for heterogeneous wireless sensor network," Expert Systems with Applications, vol. 216, p. 119448, 2023.

[23] N. Kumar et al., "THWSN: Enhanced energy-efficient clustering approach for three-tier heterogeneous wireless sensor networks," IEEE Sensors Journal, vol. 22, no. 20, pp. 20053–20062, 2022.

[24] R. Akhter and S. A. Sofi, "Precision agriculture using IoT data analytics and machine learning," Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 8, pp. 5602–5618, Sep. 2022, doi: 10.1016/j.jksuci.2021.05.013.

[25] M. A. Zamora-Izquierdo et al., "Smart farming IoT platform based on edge and cloud computing," Biosystems Engineering, vol. 177, pp. 4–17, Jan. 2019, doi: 10.1016/j.biosystemseng.2018.10.014.

[26] U. Ahmed et al., "A nutrient recommendation system for soil fertilization based on evolutionary computation," Computers and Electronics in Agriculture, vol. 189, p. 106407, Oct. 2021, doi: 10.1016/j.compag.2021.106407.

[27] E. Ahmed et al., "The role of big data analytics in Internet of Things," Computer Networks, vol. 129, pp. 459–471, Dec. 2017, doi: 10.1016/j.comnet.2017.06.013.

[28] S. Prabhu et al., "Soil analysis and crop prediction," International Journal of Scientific Research in Science and Technology, vol. 7, no. 4, pp. 117–123, 2020.

[29] Crop Recommendation Dataset. [Online]. Available: https://www.kaggle.com/atharvaingle/crop-recommendation-dataset.

[30] T. Vijayan, M. Sangeetha, A. Kumaravel, and B. Karthik, "Feature Selection for Simple Color Histogram Filter based on Retinal Fundus Images for Diabetic Retinopathy Recognition," IETE Journal of Research, vol. 69, no. 2, pp. 987–994, Feb. 2023, doi: 10.1080/03772063.2020.1844082.