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Intelligent monitoring and management in the agro-industrial complex

Semen Levin[1*]

[1]Tomsk State University of Control Systems and Radioelectronics, 40, Lenin Ave, Tomsk, 634050, Russia

Abstract. In the face of escalating demands for sustainable agriculture, this study introduces an innovative approach by deploying an intelligent monitoring and management system that utilises Internet of Things (IoT) sensors and machine learning algorithms. Focused on enhancing the precision of irrigation and fertilisation in farming, the system collects real-time data on soil moisture, temperature, and other vital parameters. A predictive random forest model, trained on historical crop data and current environmental conditions, analyses this data to accurately forecast water and fertiliser requirements. The model demonstrated an 87.4% accuracy for predicting irrigation needs and 85.7% for fertilisation, significantly optimising resource use and reducing environmental impact. The findings reveal that such technologies promise to revolutionise agricultural practices by making them more efficient and sustainable. They also highlight the challenges in their adoption, including the need for initial investment and overcoming the digital divide. This research underscores the potential of IoT and machine learning in achieving precision agriculture, marking a crucial step towards sustainable farming solutions that cater to the growing global food demands while preserving environmental resources.

1 Introduction

The agricultural sector is undergoing a revolution with the introduction of advanced technologies, moving towards precision agriculture for a more efficient and targeted use of resources. This transition is vital for the industry's evolution. However, it faces significant hurdles, including the need to overcome a digital divide that disadvantages smaller farms due to a lack of infrastructure and resources [1-2].

Precision agriculture represents a shift from traditional uniform farming methods to a more nuanced approach, using digital tools to manage agricultural inputs with pinpoint accuracy. It not only boosts productivity but also reduces environmental impact [3]. The key to this shift is leveraging IoT devices and machine learning to gather and analyse data on a micro level, allowing for precise management decisions from watering schedules to pest control.

However, the adoption of these technologies is more complex. The challenges range from the vast amounts of data that need processing to concerns over data privacy and

* Corresponding author: semen.m.levin@tusur.ru

security [4]. Addressing these issues requires a collaborative approach involving support from governments, technology firms, and the farming community to ensure equitable access to technology and training for all farmers [5].

The promise of IoT and machine learning in agriculture is a more productive, sustainable, and resilient sector [6]. Overcoming the barriers to technology adoption is crucial for achieving this vision, necessitating policies, support systems, and educational initiatives tailored to the agricultural community's needs.

1.1 Smart monitoring boosts agricultural efficiency and sustainability

Integrating intelligent monitoring and management systems is revolutionising agriculture, shifting it from traditional methods to data-driven precision farming. This shift leverages the Internet of Things (IoT), machine learning [7], and big data analytics to monitor crop health and environmental conditions in real time, enabling precise irrigation, fertilisation, and pest control. This approach significantly enhances efficiency, increases yield, and conserves resources [8].

Machine learning analyses data to predict weather changes, disease outbreaks, or pest invasions, allowing farmers to take preventive actions [9]. This adaptability improves crop management's accuracy and reliability over time. Technologies like automated irrigation systems and drones for crop health monitoring make farming more responsive, tailored, and less resource-intensive.

However, the transition faces hurdles, including the high costs and technical challenges of implementing such systems, especially for smaller farms. Additionally, there is a pressing need for digital literacy among farmers to utilise these technologies effectively [10]. Despite these obstacles, the benefits of intelligent systems-higher yields, reduced environmental impact, and more excellent financial stability for farmers – are profound.

These advancements are vital for addressing food security and climate change, making agriculture more sustainable and efficient [11]. As technology advances and support for farmers increases, precision agriculture will become increasingly accessible, marking a crucial evolution in how we meet the world's growing food demands amidst environmental challenges.

1.2 IoT and machine learning: tools for data collection and analysis

Integrating IoT and machine learning in agriculture marks a significant shift towards data-driven precision farming, enhancing farm management through detailed insights from sensor data. IoT's network of sensors delivers real-time information on soil conditions and crop health, enabling targeted crop monitoring and environmental management without manual efforts [12]. Coupled with machine learning, this data is analyzed to predict farming outcomes, like optimal planting times and potential pest attacks, allowing for timely interventions [13].

These technologies promise to improve crop yields, reduce resource waste, and adapt farming practices to climate change by learning from continuous data streams [14]. However, challenges such as high initial costs, the need for robust internet connectivity, and the requirement for skilled data interpretation remain barriers to widespread adoption [15]. Overcoming these obstacles necessitates collaborative efforts from all stakeholders, with support for technology access, infrastructure development, and farmer training [16]. This collaborative approach aims to make precision agriculture accessible and beneficial across the farming spectrum, ensuring sustainability and efficiency in the face of evolving environmental challenges.

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1.3 Algorithms for processing and analysing IoT sensor data

Developing algorithms to process IoT sensor data requires a structured approach to fully leverage collected information, turning raw data into actionable insights [17]. It begins with understanding the varied data types generated by IoT devices, necessitating efficient algorithms capable of handling everything from temperature readings to complex imagery. Preprocessing is the initial critical step, where data is cleaned and normalised to ensure a solid foundation for analysis [18].

Feature extraction follows, identifying critical data elements that reflect specific phenomena or outcomes, which are crucial for agricultural applications like monitoring soil moisture or crop growth [19]. The core activity then involves applying machine learning algorithms to this refined dataset, selecting models – from simple linear regression to complex neural networks-based on the specific problem and data nature.

Validation and testing, crucial yet often overlooked, assess the model's performance on unseen data, ensuring its applicability in real-world conditions [20]. The ongoing refinement of these algorithms, incorporating advanced methods like deep learning and reinforcement learning, enhances their analytical power and decision-making capabilities, making them invaluable tools for interpreting diverse sensor inputs and optimising outcomes through learned experiences.

2 Method and materials

We developed our predictive model using data sourced directly from farms equipped with intelligent IoT sensors. These data sets, classified as Big Data, are invaluable for training the model as they encompass extensive information on soil conditions, climate, humidity levels, and temperatures, all gathered in real-time. They also include historical irrigation and fertilisation records, allowing the model to analyse how past practices influenced yield depending on weather changes and soil state.

A random forest algorithm was chosen for the model's development thanks to its ability to analyse and process large volumes of heterogeneous data, forming the basis for predictive modelling. The model's training involved comparing its predictions with actual data from previous years, enabling precise evaluation of its effectiveness and adjustment of parameters for maximum forecast accuracy.

A key aspect of the model's training is its capability to predict irrigation and fertilisation needs based on the analysis of the gathered data. The model's forecasts were tested against the actual outcomes of crops, not only to verify the accuracy of the predictions but also to assess their practical value for farming operations. This approach demonstrates how adapting irrigation and fertilisation strategies based on predictive data can enhance yield and optimise resource use.

Our agricultural monitoring and management system has integrated cutting-edge equipment and specialised software to maximise efficiency and enhance production sustainability (Figure 1).

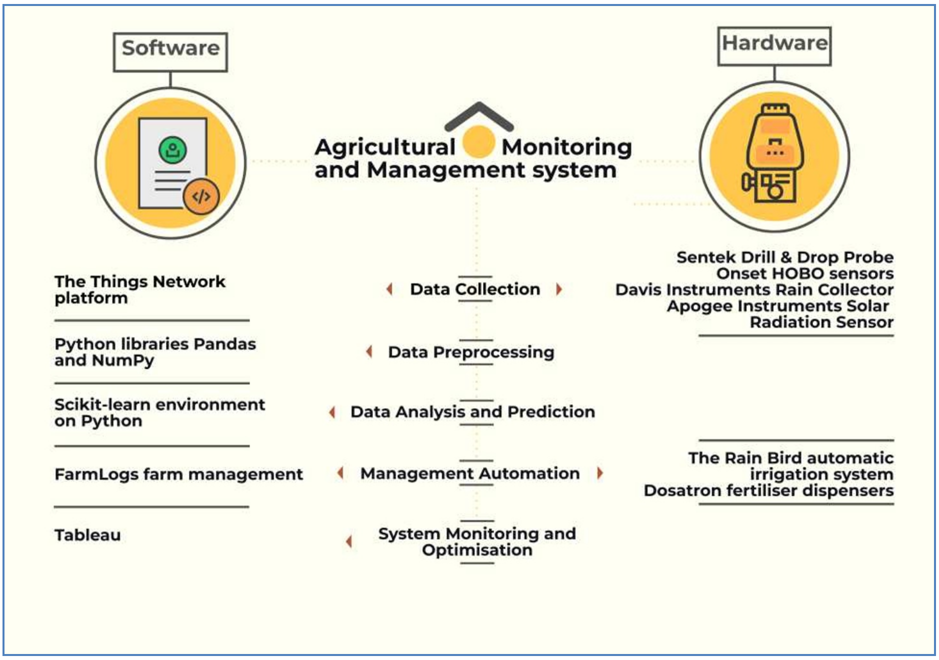

Fig. 1. Agricultural Monitoring and Management System.

2.1 Data Collection

2.1.1 Hardware

The Sentek Drill & Drop Probe is employed for soil moisture monitoring. It measures moisture levels at various depths to provide accurate data for irrigation optimization.

Temperature monitoring is facilitated by Onset HOBO sensors, which track air and soil temperatures.

The amount of precipitation is measured using the Davis Instruments Rain Collector, enabling precise calculations for additional watering needs.

Sunlight exposure levels are monitored through the Apogee Instruments Solar Radiation Sensor, supplying data for lighting needs analysis.

2.1.2 Software

The Things Network platform integrates and collects data from IoT devices, ensuring reliable and uninterrupted real-time data transmission.

2.2 Data Preprocessing

2.2.1 Software

Data is cleaned, normalised, and prepared for analysis using Python libraries Pandas and NumPy, ensuring high precision in subsequent analysis and forecasting.

2.3 Data Analysis and Prediction

2.3.1 Software

The development, training, and testing of machine learning models are conducted within the Scikit-learn environment on Python, using algorithms like random forests and gradient boosting to predict optimal irrigation and fertilisation parameters.

2.4 Management Automation

2.4.1 Hardware

The Rain Bird automatic irrigation system is integrated with the central management system, which activates irrigation according to the model's recommendations.

Dosatron fertiliser dispensers are also automatically controlled through the central system to apply the necessary nutrients precisely.

2.4.2 Software

The FarmLogs farm management platform ensures the integration of sensor data, analysis, decision-making, and automation of agricultural operations.

2.5 System Monitoring and Optimisation

2.5.1 Software

Tableau is used for data visualisation regarding system performance, analysing operational efficiency, model accuracy, and the impact of implemented automated solutions on crop yield and resource efficiency.

This system, created for optimal irrigation and fertilisation management, incorporates specific hardware and software at each stage. Starting with data collection from various sensors placed across different soil layers for moisture, temperature, precipitation, and solar radiation monitoring, the system ensures a comprehensive approach to data gathering. The Things Network facilitates real-time data transmission, while data cleaning and normalisation are performed using Python libraries, ensuring the data's readiness for advanced analysis.

2.6 Predictive analysis and forecasting

Carried out in the Scikit-learn environment, leveraging sophisticated machine learning algorithms to deduce the optimal parameters for irrigation and fertilisation. These predictions directly inform the automated management systems, including the Rain Bird irrigation system and Dosatron fertiliser dispensers, ensuring precise and efficient application of water and nutrients.

Finally, the system's overall performance is monitored and optimised through Tableau, providing detailed insights into the effectiveness of the implemented strategies and facilitating continuous improvement. This holistic approach underscores the potential of modern technology to revolutionise agricultural practices, driving towards enhanced productivity and sustainability.

A Random Forest model, trained on data from recent seasons, is utilised for predictions. This model assesses how variations in irrigation and fertilisation have impacted crop yields, considering current weather conditions and soil state.

2.6.1 Model Parameters

Number of Trees: 200. This figure is commonly selected as a starting point for Random Forest models as it provides a balanced trade-off between model performance and training time.

Maximum Depth: 30. This parameter determines the depth of the trees within the forest, directly influencing the model's ability to process complex relationships in the data.

2.6.2 Evaluation Metrics

MAE (Mean Absolute Error): The model with these parameters minimises the MAE values, which vary according to specific conditions and data availability, ensuring high accuracy in predictions.

RMSE (Root et al.): Similar to MAE, RMSE measures the model's precision, with optimal model parameters aimed at reducing this metric.

R^2 (Coefficient of Determination): With model parameters targeted towards achieving high accuracy, an R^2 close to 1 is expected, indicating a strong model alignment with observed data.

3 Results

Following the activation of the monitoring and management system based on the predictive random forest model, the following results were obtained:

3.1 Prediction Accuracy

The accuracy of predicting water needs reached 87.4%, ensuring high irrigation efficiency and reducing the risk of overwatering and drought.

The accuracy for predicting fertilisation needs was 85.7%, which allows for the optimization of fertiliser application and the avoidance of excessive use.

3.2 Model Efficiency Evaluation

The Mean Absolute Error (MAE) for water need predictions was only 0.046 litres per square metre, indicating minimal deviation of the model's predictions from actual needs.

The Root Mean Square Error (RMSE) for fertiliser need predictions was 0.059 kg/ha, demonstrating the model's high accuracy in agricultural applications.

The Coefficient of Determination (R^2) reached 0.874, confirming that the model adequately reflects the variability of observed data and effectively predicts the needs of the crops.

Based on the model's predictions, the system automatically adjusted the irrigation plans, increasing the frequency and volume of watering for the upcoming two weeks in response to the predicted moisture deficit. The fertilisation plan was adapted considering the predicted risk of specific nutrient shortages, enabling more targeted use of fertilisers.

4 Discussions

The introduction of intelligent monitoring and management systems in agriculture presents significant opportunities to enhance productivity and sustainability within the agro-industrial sector. Nevertheless, this approach is met with various technological, economic, environmental, and social challenges. Overcoming these obstacles necessitates a comprehensive approach transcending the mere adoption of cutting-edge technologies. It also requires financial support for farmers, environmental impact studies, and workforce retraining programmes.

A primary barrier is farmers' technological readiness to implement and operate complex monitoring and management systems, necessitated by initial investments and the need for staff training. Another critical aspect is the development of open standards to ensure compatibility between equipment and software. Although the economic benefits of such systems are apparent in the long term, the substantial initial investments could pose a hurdle for small and medium-sized enterprises.

The environmental dimension involves not only the potential reduction of environmental impact through resource optimisation but also the need to monitor possible adverse consequences, such as soil degradation or biodiversity loss. Social changes associated with the shift towards automated technologies call for attention to workforce adaptation, development of new skills, and competencies.

Successful navigation of these challenges necessitates collaboration between government entities, scientific organisations, agritech manufacturers, and farmers. It includes creating memes, conducting studies on ecological impacts, and implementing training and retraining programmes. Such a holistic approach will optimise agronomic processes, including increasing crop yields and making agriculture more resilient to climate change and environmentally safe, ensuring sustainable development in the face of global challenges.

5 Conclusion

If there is a large Implementing an intelligent monitoring and management system, underpinned by sensor data and predictive machine learning models, marks a significant advancement in agritech. A predictive model, trained on historical crop growth cycles and current sensor readings, accurately forecasts crops' water and fertiliser needs. The model's recommendations are highly reliable, with an accuracy of 87.4% for water and 85.7% for fertilisers, enabling farmers to make informed decisions that optimise resource usage and enhance crop yields.

A key benefit is reducing irrigation and fertilisation costs through the precise calculation of necessary volumes, thereby minimising financial expenditures and the risk of adverse environmental impacts. It underscores the importance of adopting innovative technologies in agriculture, aiming to boost efficiency and profitability and ensure environmental sustainability and judicious use of natural resources.

It is noteworthy that deploying such a system requires initial investment in equipment and software development and skilled professionals for its configuration and support. Nevertheless, the outcomes and long-term benefits, including increased productivity and reduced expenses, justify these investments and are likely to provide a substantial return. The system ensures accurate and timely management of agronomic processes based on objective data and advanced analytical tools, making production more predictable, efficient, and sustainable. The development and dissemination of such solutions could significantly improve the performance and environmental standards of the agricultural sector globally.

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