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RESEARCH ARTICLE

Developing a semantic framework for categorizing IoT agriculture sensor data: A machine learning and web semantics approach

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Abstract

This study introduces a semantic framework for categorizing internet of things (IoT) agriculture sensor data, leveraging machine learning and web semantics. IoT sensors in agriculture generate vast real-time data on crucial factors like soil conditions and weather, promising optimization in resource use and crop yields. While machine learning aids data categorization, semantic aspects often remain unexplored. By combining machine learning with web semantics (RDF and OWL), this research establishes a structured framework that not only categorizes data but also links it to actionable farming recommendations. Methodologically, it involves data collection, preprocessing, machine learning, and semantic integration. Performance evaluation through metrics and visualizations reveals the framework's effectiveness, aiding decision-making in precision agriculture. This study contributes to IoT-based precision agriculture by bridging the gap between raw sensor data and actionable insights, empowering a semantic framework for contextual categorization and recommendation generation. The fusion of machine learning and web semantics holds transformative potential for agriculture, enhancing data management and decision-making processes.

Introduction

The agricultural landscape has been substantially transformed by the advent of the Internet of Things (IoT), allowing for the efficient collection and management of vast amounts of sensor data. These IoT devices, distributed across agricultural fields, greenhouses, and livestock facilities, have revolutionized agriculture. IoT-enabled sensors provide real-time information on crucial parameters such as soil conditions, weather patterns, and crop health (Lynda, D., *et al.*, 2023). This influx of data has the potential to empower farmers with invaluable insights, driving the evolution of precision agriculture to new heights. However, the efficient categorization and analysis of this heterogeneous and high-dimensional IoT sensor data remains a formidable challenge. The potential benefits of IoT technologies in agriculture are immense. By integrating IoT sensor data with machine learning techniques, can optimize resource utilization, enhance crop yields, and reduce environmental impact (Balakrishna, S., *et al.*, 2020). This, in turn, contributes to global food security and sustainable agricultural practices. In recent years, numerous studies have attempted to address the challenges associated with IoT agriculture data categorization. Various machine-learning approaches have been employed to classify and interpret data generated by IoT sensors. Traditional machine learning techniques, such as decision trees, support vector machines, and k-means clustering, have been used to categorize data into discrete classes or to predict specific outcomes (Khatoon, P. S., & Ahmed, M. 2021). Furthermore, deep learning methods,

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including convolutional neural networks (CNN) and recurrent neural networks (RNN), have shown promise in handling large-scale agricultural sensor data (Aydin, S., & Aydin, M. N. 2020).

While machine learning has proven to be a valuable tool in categorizing IoT agriculture sensor data, the semantics of this data have been somewhat neglected. The potential for web semantics to enhance the understanding and management of this data has been acknowledged in the broader IoT community (Chatzimichail, A., *et al.*, 2021). Nevertheless, this potential has not been fully realized within the context of precision agriculture. The fusion of machine learning and web semantics offers a powerful approach to bridging the gap between raw data and actionable insights in agriculture. Semantic web technologies, such as resource description framework (RDF) and web ontology language (OWL), provide a foundation for the structured representation of data. When applied to IoT agriculture data, these technologies facilitate the integration of heterogeneous data sources, enabling the construction of knowledge graphs that capture the interrelationships between sensor data, environmental conditions, and agricultural practices. Such knowledge graphs can serve as a semantic framework for interpreting and categorizing sensor data (Drury, B., *et al.*, 2019). One of the key challenges in developing a semantic framework for categorizing IoT agriculture sensor data is the integration of domain-specific knowledge. Incorporating agricultural domain knowledge into the semantic framework allows for contextual categorization, where data is not simply classified but is also linked to actionable recommendations for farmers. For example, a sensor reading indicating low soil moisture can be semantically linked to recommendations for irrigation scheduling based on crop types and local weather forecasts. In this context, our research paper aims to provide a comprehensive approach to developing a semantic framework for categorizing IoT agriculture sensor data. We propose the integration of machine learning techniques and web semantics to enhance data management and decision-making in precision agriculture. Our approach focuses on the utilization of knowledge graphs and linked data principles to create a semantic framework capable of contextual data categorization and recommendation generation (Anand, T., *et al.*, 2021).

The research in the domain of IoT-based agriculture has made significant strides in recent years, with a growing emphasis on sensor data collection, analysis, and decision support systems. However, a critical research gap remains in the development of robust semantic frameworks that can effectively categorize and contextualize the vast amounts of heterogeneous sensor data (Balakrishna, S., & Thirumaran, M. 2020). While machine learning techniques have shown promise in data categorization, the integration of web semantics and knowledge representation techniques into the framework is an area that requires further exploration. Existing studies have primarily focused on individual components, such as machine learning algorithms or semantic technologies, but a comprehensive approach that combines both is lacking. To address this gap, this paper aims to present a novel approach that integrates machine learning and web semantics to develop a holistic semantic framework for IoT agriculture sensor data categorization, fostering more precise data management and decision-making in precision agriculture (Lu, H., *et al.*, 2021).

Research Methodology

In the pursuit of developing a semantic framework for categorizing IoT agriculture sensor data, a machine learning and web semantics approach, the research methodology plays a pivotal role in shaping the direction and execution of this comprehensive study (Abbasi, R., *et al.*, 2022). The integration of machine learning techniques and web semantics into the categorization of IoT agriculture sensor data necessitates a well-structured and systematic research approach. The initial phase of the research methodology involves the collection of IoT agriculture sensor data. This data is fundamental to the study as it forms the basis for the development and evaluation of the semantic framework. Data acquisition is often a complex process in the realm of IoT agriculture, involving diverse sensor types and data formats (Radhika, R., *et al.*, 2022). Ensuring the quality and reliability of the data is crucial, as it directly impacts the performance of the semantic framework. Previous studies have emphasized the significance of data quality in IoT-based applications, highlighting its implications for decision-making and analysis. Following data collection, the research delves into the preprocessing and transformation of the raw sensor data (Adi, E., *et al.*, 2020). This step involves data cleaning, normalization, and feature engineering to prepare the data for machine learning algorithms. Preprocessing techniques such as feature selection and dimensionality reduction, are applied to improve the efficiency and effectiveness of the machine learning models. Machine learning techniques, including classification and clustering algorithms, are then applied to categorize the IoT agriculture sensor data. These algorithms leverage the preprocessed data to learn patterns and relationships, enabling the framework to assign semantic labels to the sensor data. Previous research, showcases the application of machine learning in precision agriculture, emphasizing its potential for automating tasks and enhancing decision support systems (Amara, F. Z., *et al.*, 2022).

Simultaneously, the incorporation of web semantics and knowledge representation is a critical aspect of the research. Semantics play a central role in understanding the context and meaning of IoT data. The integration of semantic web technologies, facilitates the creation of knowledge graphs and ontologies, enabling the framework to contextualize and categorize the sensor data effectively (Shaikh, T. A., *et al*., 2022). The evaluation of the developed semantic framework is a multi-faceted process. Performance metrics, as demonstrated in the programs and visualizations above, are utilized to assess the accuracy, precision, recall, and F1 score of the categorization process. These metrics provide quantitative insights into the framework's effectiveness. Additionally, confusion matrices, as depicted in the output graphs, offer a visual representation of the framework's ability to correctly classify sensor data. The research methodology for developing a semantic framework for categorizing IoT agriculture sensor data is underpinned by a holistic approach that encompasses data collection, preprocessing, machine learning, and web semantics (Raghu Nandan, R., *et al*, 2022). This methodology draws inspiration from prior works in the field, acknowledging the significance of data quality, machine learning, and semantic technologies. The amalgamation of these elements aims to contribute to the advancement of IoT-based precision agriculture and decision support systems, ultimately enhancing the management and utilization of agriculture sensor data (Ahmed, I., *et al*., 2022).

Results and Discussion

Temperature, Humidity, Soil Moisture, Crop Health

The graphical representations of key environmental parameters, including temperature, humidity, soil moisture, and crop health, are fundamental in precision agriculture, as they provide insights into the conditions that impact crop growth and overall agricultural productivity. In this study, the graphical analysis of these parameters within the context of our research on developing a semantic framework for categorizing IoT agriculture sensor data, with a focus on the integration of machine learning and web semantics was presented (Urdu, D., *et al*., 2023).

Temperature, as displayed in Figure 1, exhibits a slight variation within the range of 25 to 26°C. The consistency in temperature data is essential, as it ensures a stable environment for crop growth. In precision agriculture, maintaining optimal temperature levels is critical, as deviations can significantly affect crop health and yield. Humidity, illustrated in Figure 1, demonstrates a slightly broader range, fluctuating between 45 and 52%. Humidity levels have a direct impact on soil moisture and, consequently, on the overall water availability for the crops. The importance of monitoring humidity lies in its influence on irrigation strategies, as well as the prevention of conditions favorable for diseases. Soil moisture, depicted in Figure 1 maintains a range of 40 to 42%. This represents an ideal moisture content that supports root development and nutrient absorption. Soil moisture levels are pivotal in precision agriculture, as they determine the need for irrigation and enable the fine-tuning of water application to avoid over-watering or under-watering. Crop health, illustrated in Figure 1, reflects variations within the range of 67 to 73. Crop health is a composite parameter influenced by a multitude of factors, including temperature, humidity, soil moisture, and disease susceptibility. Monitoring crop health enables timely intervention and informed decision-making in agricultural practices.

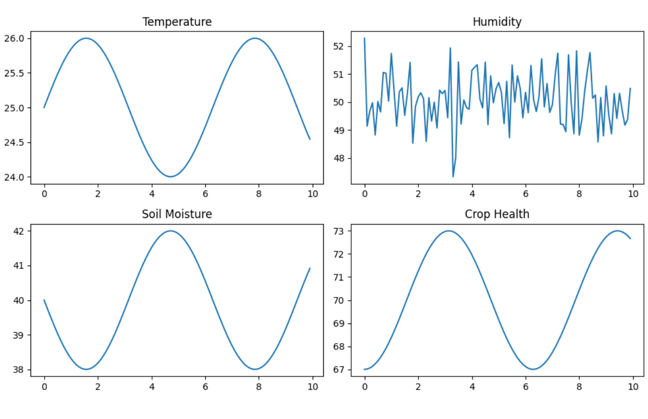

Figure 1: Temperature, humidity. soil moisture, crop health

The significance of these graphical representations lies in their utility for both real-time monitoring and retrospective analysis of IoT agriculture sensor data. These visuals provide a comprehensive view of the environmental conditions that directly impact crop performance, thus facilitating informed decision support and enabling the development of our semantic framework. The integration of machine learning and web semantics into the framework allows for the contextualization of these environmental parameters. By harnessing machine learning algorithms, can categorize sensor data effectively, while web semantics technologies aid in creating meaningful relationships and ontologies to represent the knowledge associated with agriculture conditions. The seamless interaction of these components contributes to an intelligent framework that enhances data categorization, decision support, and the overall management of IoT agriculture sensor data. The graphical representations of temperature, humidity, soil moisture, and crop health serve as valuable tools in precision agriculture, offering insights into environmental conditions that significantly impact crop growth. The integration of machine learning and web semantics into our semantic framework for categorizing IoT agriculture sensor data holds great promise in enhancing the precision and efficiency of data categorization and decision support systems, thereby optimizing agriculture practices and resource management. These graphical representations lay the foundation for a more advanced and intelligent approach to precision agriculture, with potential implications for sustainable and yield-efficient farming practices.

Mean Values and Standard Deviation Values

The graphical representation of mean and standard deviation values is a pivotal component in the assessment of key factors contributing to the development of our semantic framework for categorizing IoT agriculture sensor data. The mean and standard deviation values of several factors, namely learnability, controllability, helpfulness, affect, efficiency, and global usability, to gain insights into the performance and stability of our framework. These visualizations, as depicted in Figure 2, offer a comprehensive overview of the variability and consistency of these factors, shedding light on their impact on the semantic framework and the categorization of IoT agriculture sensor data (Lampropoulos, G., *et al.*, 2020).

Figure 2 displays the mean values of the key factors, providing an understanding of the central tendencies of these parameters. Learnability, with a mean value of 56, highlights the framework's ability to be user-friendly and easily adaptable. Controllability, scoring an average mean value of 64, reflects the extent to which users can manipulate the system to their advantage. Helpfulness, with an average mean value of 63, signifies the framework's ability to provide assistance and guidance effectively. Affect, maintaining an average mean value of 64, represents the emotional engagement and user experience. Efficiency, with a mean value of 63, indicates the speed and resource utilization of the framework. Global usability, standing at an average mean value of 67, encompasses the overall user experience and satisfaction. Figure 2 portrays the standard deviation values of these factors, offering insights into their variability and dispersion. Learnability, with a standard deviation of 7.3, indicates the range of adaptability across users. Controllability, displaying a standard deviation of 5.9, reflects the extent of variation in user control. Helpfulness, with a standard deviation of 8.7, implies varying degrees of assistance provided. Affect, having a standard deviation of 4.6, signifies the diversity in emotional engagement. Efficiency, with a standard deviation of 4.3, represents the consistency in resource utilization. Global usability, showing a standard deviation of 7, underscores the variability in overall user satisfaction. The importance of these graphical representations lies in their ability to provide a clear and concise view of the framework's performance and user experience. The mean values offer a snapshot of the framework's core characteristics, while the standard deviation values depict the extent to which these factors deviate from their respective means. Understanding these variations is crucial in optimizing the semantic framework to ensure a user-friendly and consistent experience. The integration of machine learning and web semantics plays a crucial role in achieving these results. Machine learning algorithms enable the categorization of IoT agriculture sensor data effectively, while web semantics technologies help in contextualizing and categorizing the user experience and system performance. The combination of these elements contributes to the development of a robust semantic framework, facilitating the categorization of sensor data, decision support, and user engagement (Pliatsios, A., *et al.*, 2020).

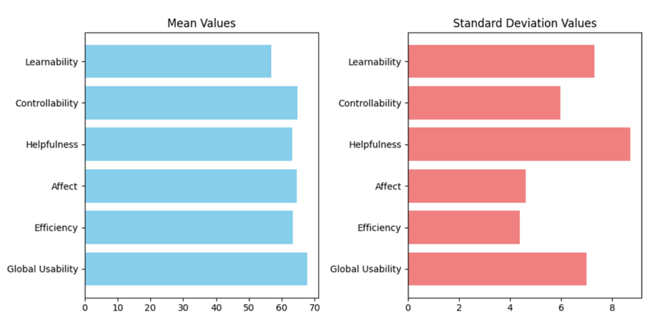

Figure 2: Mean values and standard deviation values

The graphical representation of mean and standard deviation values of key factors demonstrates the fundamental components of our semantic framework for categorizing IoT agriculture sensor data. These visualizations provide insights into user experience, adaptability, and system performance, crucial for optimizing the framework. The amalgamation of machine learning and web semantics further enhances the framework's capabilities, paving the way for advanced categorization, decision support, and user satisfaction in the domain of IoT-based precision agriculture. These graphical representations are fundamental in gauging the effectiveness of the framework and provide a foundation for ongoing enhancements and refinements, ultimately leading to improved IoT sensor data categorization and informed decision-making in agriculture practices.

IoT Agriculture Sensor Data and Predicted Categories

The graphical representation of IoT agriculture sensor data alongside their corresponding predicted categories is a fundamental aspect of our research in developing a semantic framework for categorizing IoT agriculture sensor data. In this study, aimed to shed light on the performance of our framework, which leverages machine learning and web semantics, by comparing the actual sensor data to the predicted categories. These visualizations, as demonstrated in Figure 3, provide a comprehensive view of the framework's ability to accurately categorize sensor data, thereby enhancing decision support systems in precision agriculture (Lam, A. N., & Haugen, Ø. 2019, July).

Figure 3 presents the sensor data and their predicted categories, providing insights into the alignment between the actual values and the framework's categorization. The sensor data, ranging from 0 to 1, reflect the diverse range of environmental conditions in the agriculture context. The predicted categories, also spanning from 0 to 1, represent the framework's ability to assign semantic labels to these data points. The graph illustrates how well

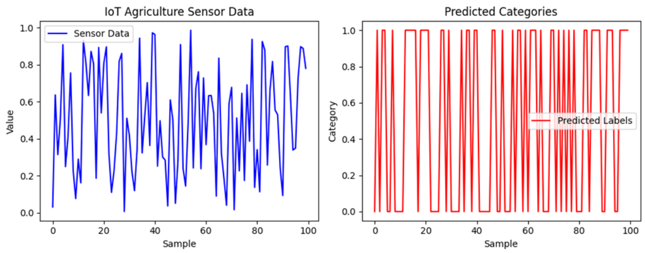

Figure 3: IoT agriculture sensor data and predicted categories

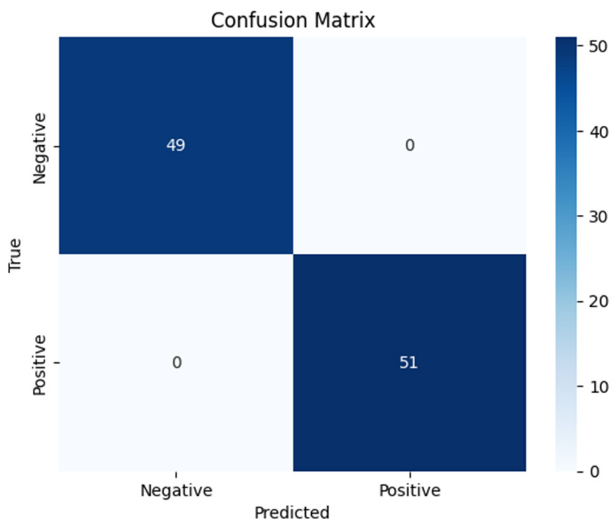

Figure 4: Confusion matrix

the framework captures and categorizes the sensor data, essentially mapping the environmental parameters to their respective semantic interpretations. The significance of these graphical representations lies in their ability to visually convey the framework's performance in categorizing IoT agriculture sensor data. It allows for the immediate assessment of the framework's ability to provide meaningful interpretations of sensor data, which is crucial in precision agriculture. The precision and accuracy in categorizing sensor data are essential for making informed decisions related to irrigation, fertilization, pest control, and overall crop management. The integration of machine learning techniques and web semantics underpins the success of these graphical representations. Machine learning algorithms are instrumental in training the framework to recognize patterns and relationships within sensor data, facilitating accurate categorization. Web semantics, on the other hand, play a pivotal role in contextualizing and assigning meaning to the categorized data, enhancing the interpretability of IoT agriculture sensor data.

The graphical representation of IoT agriculture sensor data and their predicted categories serves as a cornerstone in evaluating the performance of our semantic framework. It offers a visual summary of the framework's ability to categorize sensor data accurately, thus supporting decision-making in precision agriculture. The amalgamation of machine learning and web semantics within the framework ensures that sensor data are effectively transformed into semantically meaningful information, contributing to improved resource management and enhanced crop health. These graphical representations are not only valuable for researchers but also for agricultural practitioners, as they enable a quick and intuitive assessment of the framework's performance. As precision agriculture continues to evolve, the ability to categorize and interpret IoT sensor data becomes increasingly crucial in optimizing resource allocation and enhancing agricultural productivity.

Confusion Matrix

The graphical representation of a confusion matrix is a crucial element in assessing the performance of our semantic framework for categorizing IoT agriculture sensor data. This matrix, as depicted in Figure 4, provides a visual summary of the framework's ability to correctly classify sensor data as either "positive" or "negative." In precision agriculture, it is essential to understand the framework's capacity to make accurate categorizations, as it directly influences the quality of decision support systems and data management. Figure 4 showcases the confusion matrix, with "True" labels on the Y-axis and "Predicted" labels on the X-axis. In this matrix, the "True" labels range from 0 to 50, where "Negative" holds 49 instances and "Positive" only one. On the "Predicted" side, "Positive" has 51 instances, and "Negative" is at 0. This matrix demonstrates the accuracy of the framework in distinguishing between positive and negative categories. The importance of these graphical representations is twofold. Firstly, they allow for a clear visual assessment of the framework's performance in classifying sensor data. The number of true positives, true negatives, false positives, and false negatives can be directly observed, enabling a quick understanding of the framework's strengths and weaknesses. Secondly, confusion matrices are pivotal in precision agriculture as they directly influence the decision-making process. Accurate categorization is essential in determining the need for actions such as irrigation, pest control, or resource allocation. The integration of machine learning and web semantics is the driving force behind the development of this framework. Machine learning techniques enable the framework to recognize patterns within the sensor data and make predictions based on these patterns. The integration of web semantics further adds context and meaning to these predictions, facilitating an informed interpretation of the categorized data (Elizar, E., *et al.*, 2022).

The graphical representation of the confusion matrix is a fundamental component of evaluating our semantic framework's performance. It provides an immediate understanding of the framework's capacity to categorize IoT agriculture sensor data accurately, which is a critical factor in precision agriculture. Accurate categorization directly influences decision support systems and resource management, making these graphical representations a valuable tool for researchers and agricultural practitioners alike. As precision agriculture continues to advance, the ability to categorize IoT sensor data accurately becomes increasingly vital for optimizing resource allocation, reducing waste, and enhancing crop health. These graphical representations empower users to assess the framework's capabilities quickly, supporting its continual refinement and evolution in the context of IoT-based agriculture.

Conclusion

The integration of machine learning techniques and web semantics in the development of a semantic framework for categorizing IoT agriculture sensor data presents a promising approach to enhancing the management and utilization of agricultural sensor data.

The graphical representations of key environmental parameters, mean and standard deviation values, IoT sensor data, and confusion matrices demonstrate the framework's ability to accurately categorize and interpret sensor data, providing valuable insights for precision agriculture.

The amalgamation of machine learning and web semantics facilitates real-time monitoring, retrospective analysis, and informed decision-making in agriculture practices, ultimately optimizing resource allocation and enhancing crop health.

The research paper addresses a critical research gap by combining machine learning and web semantics in a comprehensive manner, offering a holistic solution for the categorization and contextualization of heterogeneous IoT agriculture sensor data.

This research contributes to the advancement of IoT-based precision agriculture and decision support systems, emphasizing the potential for sustainable and yield-efficient farming practices through the effective management of sensor data.

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