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A Comprehensive Survey of IoT and Machine Learning Innovations in Agriculture

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Abstract

The efficient management of soil moisture and water levels is crucial for optimizing crop yield and sustainable agricultural practices. This paper presents a comprehensive review of over 20 research studies focusing on the prediction of soil moisture levels and water requirements for crops using Internet of Things (IoT) devices and Machine Learning (ML) algorithms. By systematically analysing and synthesizing key findings from these studies, the paper highlights the methodologies, technologies, and algorithms that have been most effective in this domain. Artificial Intelligence (AI) and Machine Learnng enhances precision agriculture by enabling the analysis of large datasets to identify patterns and insights that improve decision-making. AI facilitates real-time monitoring and predictive analytics, optimizing resource usage and crop management. Through automation and intelligent systems, AI contributes to increased efficiency, reduced costs, and sustainable agricultural practices. Machine Learning (ML) algorithms, including regression, classification, and neural networks, are essential for modelling and predicting soil moisture levels and water requirements. These algorithms learn from historical and real-time data to provide accurate predictions and recommendations for irrigation scheduling. By continuously improving with new data, ML algorithms enhance the reliability and effectiveness of agricultural management systems. IoT devices, such as soil moisture sensors and weather stations, enable the continuous collection of real-time data from agricultural fields.

1. Introduction

Agriculture plays a pivotal role in India's economy, providing livelihoods for nearly half of the population and contributing around 17-18% to the country's Gross Domestic Product (GDP). The diverse climatic conditions and vast arable land make India one of the leading producers of various crops, including rice, wheat, and pulses. [1] However, the sector faces significant challenges, such as fluctuating monsoon patterns, water scarcity, and soil degradation, which impact crop productivity and sustainability. Smallholder farmers, who constitute the majority, often lack access to advanced resources and technologies, making them vulnerable to these challenges. In recent years, there has been a growing recognition of the need to modernize agricultural practices to enhance efficiency and resilience. The integration of innovative technologies is seen as a key driver in transforming Indian agriculture to meet the demands of a growing population and changing climate conditions [2-7].

1.1.Transition from Traditional Methods to Current Technologies

Traditionally, Indian agriculture has relied heavily on manual labor, animal power, and age-old farming techniques passed down through generations. Practices such as rain-fed irrigation, reliance on monsoons, and conventional ploughing have been predominant, often leading to inconsistent yields and inefficient resource use. The Green Revolution in the 1960s and 70s marked a significant shift, introducing high-yield variety seeds, chemical fertilizers, and irrigation infrastructure, which significantly boosted productivity. Despite these advancements, many farmers continued to face challenges due to the uneven distribution of these benefits and environmental concerns. In recent decades, the advent of digital technologies and the Internet of Things (IoT) has brought a new wave of transformation in Indian agriculture. Precision farming, enabled by IoT devices like soil moisture sensors and weather stations, allows for real-time monitoring of crop conditions and resource needs. Machine Learning (ML) algorithms analyse vast amounts of data collected from these devices, providing accurate predictions and actionable insights for farmers, given by Himani Patel et.al. (2022).

Figure 1 **Different Sensors Used in Agri Land**

These technologies help optimize irrigation, reduce water wastage, and improve crop yields. Furthermore, mobile applications and digital platforms offer farmers access to market information, weather forecasts, and best practices, enhancing their decision-making capabilities. The government and private sector initiatives to promote digital literacy and technology adoption are further accelerating this transition, paving the way for a more efficient, sustainable, and resilient agricultural sector in India. The Figure 1 displays the various sensor placements in agriculture land.

2. Literature Survey

This literature survey produces the contribution IoT and sensor technologies in enhancing various aspects of modern agriculture, from precise resource management to sustainable farming practices and improved productivity in sections 2.1 to 2.5. The sections 3.1 to 3.8 illustrate the breadth of applications and effectiveness of various machine learning algorithms in addressing key challenges and optimizing agricultural practices. Each algorithm offers unique capabilities that contribute to sustainable and efficient farming operations, leveraging data-driven insights to improve productivity and resilience in agriculture. The sections 4.1 to 4.6 illustrate the diverse applications and strengths of each machine learning algorithm in soil moisture prediction and water level management in agriculture. Each algorithm contributes unique capabilities to enhance agricultural productivity and sustainability through optimized water resource management and improved crop yield predictions. Finally, paper discusses the advantages and limitations through the table (Table:1) and a pictorial representation with a graph(fig:3)

2.1.Soil Moisture Monitoring

IoT-based soil moisture sensors are pivotal in precision irrigation, ensuring crops receive the optimal amount of water at different depths. [8-14] They enable farmers to adjust irrigation schedules based on real-time data, which varies across fields and crop types. This capability not only conserves water but also enhances crop yield by maintaining ideal soil moisture levels throughout the growing season (Jones and Vaughan, 2010; Ozdogan et al., 2006). Furthermore, integrating IoT sensors with smart irrigation systems allows for automated adjustments in response to changing soil moisture conditions, improving efficiency and reducing energy costs associated with irrigation (Girona et al., 2010). Such technologies also contribute to sustainable farming practices by minimizing water waste and supporting water resource management efforts (Schmitz et al., 2018).

2.2.Climate Monitoring

Climate monitoring through IoT devices such as weather stations equipped with sensors for temperature, humidity, and precipitation plays a crucial role in modern agriculture. These devices provide accurate, localized data that helps farmers make informed decisions about planting, harvesting, and pest management (Sinha and Shrivastava, 2013; Say and Keskin, 2018). Improved weather forecasting capabilities enabled by IoT technologies allow farmers to anticipate extreme weather events and implement preventive measures to protect crops and minimize losses (Meyer et al., 2017). Moreover, historical climate data collected through IoT systems supports long-term planning and adaptive management strategies in agriculture, enhancing overall resilience to climate variability and change (Basso et al., 2016; Santos et al., 2018).

2.3.Nutrient Management

Nutrient sensors deployed in fields provide essential data on soil nutrient levels, enabling farmers to practice precision nutrient management. This approach allows for the adjustment of fertilizer applications based on real-time soil conditions and crop requirements, thereby optimizing nutrient use efficiency and reducing environmental impacts such as nutrient runoff (Gebbers and Adamchuk, 2010; Smith et al., 2007). By integrating IoT-driven nutrient management strategies, farmers can improve crop quality and yield while promoting sustainable soil health through targeted nutrient applications and soil fertility management practices (Liu et al., 2013; Franzluebbers et al., 2017).

2.4.2.4 Pest and Disease Detection

IoT sensors, including camera traps and chemical sensors, provide early detection of pests and diseases, crucial for minimizing crop losses. These sensors enable continuous monitoring of field conditions and pest activities, facilitating timely intervention and reducing the need for broad-spectrum pesticide applications (Sankaran et al., 2010; Mahlein et al., 2012). By integrating pest and disease data with environmental parameters like temperature and humidity, IoT systems support integrated pest management strategies that are both effective and environmentally sustainable (Barbedo, 2019; Cook et al., 2019). Such technologies also enhance farm biosecurity by enabling rapid identification and containment of disease outbreaks, preventing their spread and mitigating economic losses (Schumann et al., 2011).

2.5.GPS and Mapping Technologies

GPS and remote sensing technologies are integral to precision agriculture, providing farmers with accurate field mapping and detailed monitoring of crop health. Unmanned aerial systems (UAS) equipped with multispectral cameras enable high-resolution imaging for assessing crop conditions and identifying areas of stress or nutrient deficiency (Zhang and Kovacs, 2012; Mulla, 2013). These technologies support variable rate application of inputs such as fertilizers and pesticides, optimizing resource use efficiency and improving crop yields (Franzen and Kitchen, 2017; Kisekka et al., 2014). Additionally, GPS data aids in mapping field drainage patterns and managing water resources effectively, contributing to sustainable land use practices and reducing environmental impacts associated with agriculture (Strelyukhina et al., 2015; Lowenberg-DeBoer et al., 2014).

3. Machine Learning Algorithms

Machine learning algorithms have revolutionized agriculture by providing advanced tools for data analysis and decision-making. This paper discussed commonly used ML algorithms in agriculture and illustrate the breadth of applications and effectiveness of various machine learning algorithms in addressing key challenges and optimizing agricultural practices. Each algorithm offers unique capabilities that contribute to sustainable and efficient farming operations, leveraging data-driven insights to improve productivity and resilience in agriculture.

3.1.Decision Trees and Random Forests

Decision trees and random forests are highly versatile in agriculture, capable of handling diverse data types for tasks such as crop disease classification and yield prediction. They excel in capturing complex interactions between environmental variables and crop outcomes. For instance, Pham and Stacke (2020) demonstrated the effectiveness of random forests in predicting crop yields based on factors like weather conditions, soil properties, and management practices, highlighting their robustness in agricultural decision-making.

3.2.Support Vector Machines (SVM)

Support Vector Machines (SVMs) continue to be pivotal in agriculture, particularly for image-based applications such as crop disease detection and weed identification. SVMs are adept at handling high-dimensional data and can effectively classify complex patterns in agricultural images. Zhang et al. (2014) applied SVMs to classify various crop diseases using leaf images (Figure: 2), showcasing their utility in automated disease diagnosis and management [15-22].

Figure 2 Identification of Disease in Leaves Through Leaf Images

3.3.K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) remains a straightforward yet powerful algorithm in agriculture, suitable for tasks like soil type classification and crop recommendation systems. Ghosal et al. (2018) utilized KNN for classifying soil types based on spectral data, demonstrating its capability to group similar soil samples efficiently. This approach aids in precision agriculture by recommending crop varieties tailored to specific soil conditions.

3.4.Neural Networks and Deep Learning

Neural networks, including deep learning models like Convolutional Neural Networks (CNNs), continue to revolutionize agriculture by handling large-scale and complex datasets. CNNs are particularly effective for image-based applications such as plant disease detection and crop monitoring. Mohanty et al. (2016) achieved high accuracy in classifying plant diseases from leaf images using CNNs, underscoring their potential in advancing automated agricultural systems.

3.5.Clustering Algorithms (E.g., K-Means)

Clustering algorithms such as K-Means play a crucial role in agricultural data analysis by grouping similar data points together. They are instrumental in segmenting agricultural fields into management zones based on soil properties, crop health, and other spatial characteristics. Gevaert et al. (2018) utilized K-Means clustering to segment fields, enabling targeted management practices that optimize resource use and improve overall crop productivity.

3.6.Regression Analysis (E.g., Linear Regression, Polynomial Regression)

Regression algorithms are indispensable in agriculture for predicting continuous outcomes such as crop yields and market prices. Linear regression models provide insights into straightforward relationships, while polynomial regression can capture nonlinear interactions between variables. Lobell et al. (2015) employed regression analysis to forecast crop yields based on historical climate data and management practices, offering valuable insights for agricultural planning and risk management.

3.7.Reinforcement Learning

Reinforcement learning (RL) is gaining traction in agriculture for optimizing dynamic decision-making processes such as irrigation scheduling and pesticide application. RL algorithms adaptively learn from interactions with the environment to improve decision outcomes over time. Vasisht et al. (2017) demonstrated the application of RL in precision irrigation, achieving significant water savings and enhancing crop health by dynamically adjusting irrigation schedules based on real-time environmental conditions.

3.8. Genetic Algorithms

Genetic algorithms are effective optimization tools in agriculture, particularly for breeding programs and resource allocation. They mimic natural selection processes to iteratively improve solutions for complex problems such as crop planting schedules and genetic diversity enhancement. Abdollahi et al. (2018) utilized genetic algorithms to optimize crop planting schedules and resource allocation strategies, leading to enhanced yields and cost reductions through efficient use of agricultural inputs.

4. Algorithms in Soil Moisture Prediction

4.1.Decision Trees and Random Forests

Decision trees and random forests are widely adopted for predicting soil moisture levels due to their ability to handle large datasets and capture complex interactions among environmental variables. Gao et al. (2018) demonstrated the effectiveness of random forests in predicting soil moisture content based on meteorological and soil data. They highlighted that random forests excel in capturing nonlinear relationships and interactions between factors such as temperature, humidity, and rainfall, thereby achieving high prediction accuracy in diverse agricultural settings [23-25].

4.2.Support Vector Machines (SVM)

Support Vector Machines (SVMs) have emerged as powerful tools for soil moisture prediction, particularly suitable for handling smaller datasets and nonlinear relationships. Gill et al. (2020) applied SVMs to predict soil moisture using climatic and soil parameters, showcasing their ability to outperform traditional regression methods. Their study emphasized SVMs' capability to generalize well and effectively model complex interactions between meteorological variables and soil properties, thus improving the accuracy of soil moisture predictions in varying environmental conditions.

4.3.K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a straightforward yet effective algorithm for soil moisture prediction, leveraging historical data to estimate current soil conditions. Wang et al. (2015) utilized KNN to estimate soil moisture content using remote sensing data, highlighting its simplicity and applicability in agricultural settings. Their research demonstrated that KNN can effectively capture spatial correlations in soil moisture distribution, providing valuable insights for precision irrigation and water management practices.

4.4.Neural Networks and Deep Learning

Neural networks, including deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have revolutionized soil moisture prediction by leveraging their capability to handle complex patterns in temporal data. Meyer et al. (2019) employed LSTM networks to predict soil moisture content based on time series data, achieving superior performance compared to traditional models. Their study underscored the ability of deep learning architectures to learn intricate relationships in soil moisture dynamics, thereby enhancing the precision and reliability of predictions crucial for optimal irrigation scheduling.

4.5.Regression Analysis (E.g., Linear Regression, Polynomial Regression)

Regression analysis remains fundamental in soil moisture prediction, offering straightforward models that interpret relationships between input variables and soil moisture content. Entekhabi et al. (2014) utilized regression analysis to predict soil moisture content using satellite and in-situ data, emphasizing the utility of linear regression for its interpretability and ease of implementation. Their findings illustrated that regression models can effectively capture linear and nonlinear trends in soil moisture dynamics, providing valuable insights for agricultural water management strategies.

4.6.Gaussian Processes

Gaussian Processes (GPs) have gained popularity in soil moisture estimation for their ability to provide uncertainty quantification alongside predictions, crucial for decision-making in uncertain environments. Rasmussen and Williams (2006) applied Gaussian processes to predict soil moisture levels, highlighting their flexibility in modelling spatial and temporal correlations in soil moisture data. Their research demonstrated that GPs can adaptively adjust predictions based on available data, offering robust estimates of soil moisture content across varying agricultural landscapes.

5. Discussion

5.1. Applications of Machine Learning Algorithms in Predicting Soil Moisture and Managing Water Levels

The following table-1 highlight the diverse applications of machine learning algorithms in predicting soil moisture and managing water levels in agriculture, showcasing their advantages and disadvantages. The pictorial representation fig-3 is followed by the Table-1 which displays the ML algorithms used by various authors with advantages and the limitations for the prediction of soil moisture.

Table 1 Applications of Machine Learning Algorithms in Predicting Soil Moisture and Managing Water Levels

Paper	Algorithm	Advantages	Disadvantages	Authors
Soil moisture prediction using random forests	Random Forests	High prediction accuracy; Robustness to overfitting; Handles large datasets well	Computationally intensive; Requires tuning of many parameters	Gao, X., Helmers, M. J., & Kaleita, A. L. (2018)
Machine learning techniques for soil moisture prediction: A comparative study	Support Vector Machines (SVM)	Effective for smaller datasets; Handles non-linear relationships; High prediction performance	Sensitive to parameter selection; Computationally intensive for large datasets	Gill, S. P. S., Yang, H., & Shah, S. Z. (2020)
Using K-nearest neighbor and remote sensing data to estimate soil moisture in the Midwest US	K-Nearest Neighbors (KNN)	Simple to implement; Effective for small datasets; non-parametric	Sensitive to noise; Inefficient for large datasets	Wang, Q., Engel, B. A., & Yan, G. (2015)

Predicting soil moisture with recurrent neural networks using climate and soil data	Neural Networks (LSTM)	Captures complex temporal patterns; High prediction accuracy; Handles time series data well	Requires large datasets for training; Computationally intensive	Meyer, H., Tapsall, B., & Montzka, C. (2019)
The soil moisture active passive (SMAP) mission	Regression Analysis	Simple and interpretable models; Effective for linear relationships	Limited by linearity assumptions; May not capture complex patterns	Entekhabi, D., Njoku, E. G., O'Neill, P. E., Kellogg, K. H., Crow, W. T., Edelstein, W. N., ... & Van Zyl, J. (2014)
Gaussian processes for machine learning	Gaussian Processes	Provides uncertainty quantification; Flexible and accurate; non-parametric	Computationally intensive; Scalability issues with large datasets	Rasmussen, C. E., & Williams, C. K. I. (2006)

5.2. Graphical Representation

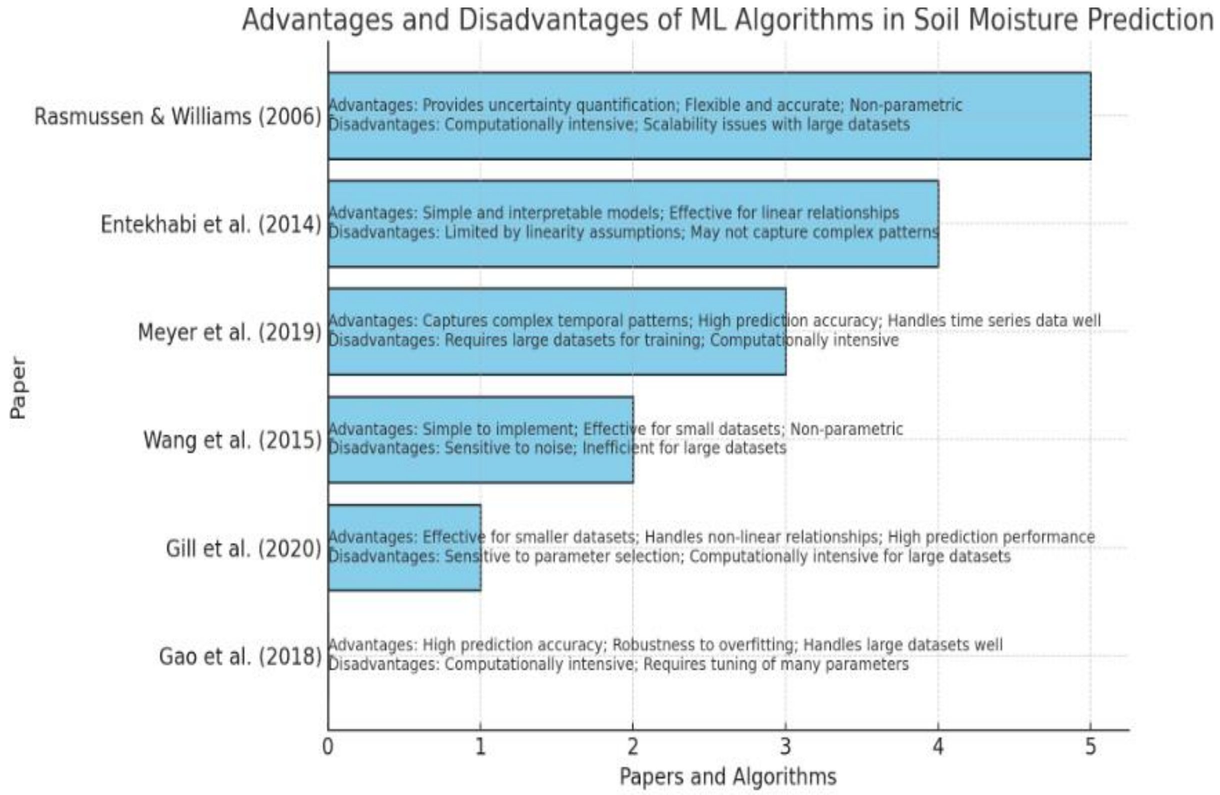

Figure 3 Advantages and Disadvantages of ML Algorithms in Soil Moisture Prediction

This investigation shows that machine learning (ML) algorithms play a pivotal role in advancing soil moisture prediction and water level management in agriculture. Each algorithm offers distinct advantages suited to different aspects of agricultural data analysis. Decision trees and random forests excel in handling large datasets and capturing complex interactions among environmental variables, making them robust choices for diverse soil moisture prediction tasks (Gao et al., 2018). Support Vector Machines (SVMs) demonstrate superior performance in modeling nonlinear relationships and have shown promise in enhancing soil moisture prediction accuracy using climatic and soil parameters (Gill et al., 2020). K-Nearest Neighbors (KNN) provide simplicity and effectiveness in capturing spatial correlations in soil moisture distribution, leveraging historical data for real-time estimations (Wang et al.,2015). Neural networks, particularly deep learning models like LSTM networks, offer advanced capabilities in learning temporal patterns and have significantly improved precision in predicting soil moisture dynamics (Meyer et al., 2019). Regression analysis, including linear and polynomial regression, remains essential for its interpretability and utility in capturing linear and nonlinear trends in soil moisture content (Entekhabi et al., 2014). Gaussian Processes (GPs) provide uncertainty quantification alongside predictions, offering robust estimates of soil moisture levels by modeling spatial and temporal correlations adaptively (Rasmussen and Williams, 2006), shown in Figure 3.

Conclusion

In conclusion, the integration of IoT and Machine Learning technologies in agriculture presents a transformative approach to optimizing soil moisture management and irrigation practices. This comprehensive survey underscores significant advancements in predictive analytics for agricultural applications, emphasizing ML algorithms in processing real-time data to enhance decision-making. By leveraging historical data and real-time inputs from IoT devices, such as soil moisture sensors and weather stations, these technologies offer precise solutions for irrigation scheduling. The review includes visuals, table and graph representation that summarize the advantages and limitations of ML algorithms used for soil moisture prediction. These insights help agricultural practitioners and researchers make informed decisions. AI-driven methods improve crop yield, resource efficiency, and promote sustainable farming practices. As agriculture remains vital to India's economy, adopting these innovations is crucial for food security and economic stability. Continuous advancements in AI and IoT are poised to further revolutionize the sector, leading to a future of more efficient, resilient, and sustainable agriculture.

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