Optimizing irrigation and nutrient management in agriculture through artificial intelligence implementation

Abstract:

Agriculture plays a pivotal role in sustaining global food security and addressing the challenges of a growing population. However, the efficient use of water and nutrients in agriculture is crucial to mitigate environmental impact while maximizing crop yield. In recent years, the integration of artificial intelligence (AI) techniques into agricultural practices has gained momentum, offering innovative solutions for optimizing irrigation and nutrient management. This review paper examines the diverse applications of AI in agriculture, focusing on its role in enhancing irrigation scheduling and nutrient management for improved productivity and resource conservation. The paper presents an overview of various AI technologies, such as machine learning, remote sensing, and data analytics, and their contributions to sustainable agricultural practices. It also discusses the challenges and opportunities associated with the adoption of AI in agriculture, including data quality, model interpretability, and farmer acceptance. Through a comprehensive analysis of recent research and case studies, this review underscores the potential of AI to revolutionize irrigation and nutrient management strategies, ultimately fostering a more resilient and productive agricultural sector.

Key words: Artificial Intelligence Implementation, nutrient management, global food security, AI agriculture

1. Introduction:

Agriculture plays a significant role in the economic sector. The automation in agriculture is the main concern and the emerging subject across the world. The population is increasing tremendously and with this increase the demand of food and employment is also increasing. The traditional methods which were used by the farmers, were not sufficient enough to fulfil these requirements. Thus, new automated methods were introduced. Artificial Intelligence in agriculture has brought an agriculture revolution. This technology has protected the crop yield from various factors like the climate changes, population growth, employment issues and the food security problems. various applications of Artificial intelligence in agriculture such as for irrigation, weeding, spraying with the help of sensors and other means embedded in robots and drones. These technologies save the excess use of water, pesticides, herbicides, maintains the fertility of the soil, also helps in the efficient use of man power and elevate the productivity and improve the quality.

Agriculture faces the dual challenge of increasing food production to meet the demands of a growing population while minimizing its environmental impact. Water scarcity and improper nutrient management are significant issues affecting crop yield and resource utilization. The emergence of AI as a transformative technology has opened avenues to address these challenges by optimizing irrigation and nutrient management practices.

Agriculture industry can experience rapid growth by adopting advanced technologies to bolster the yield of the crops. Accessibility to a large number of equipment and state-of-the-art technologies like Artificial Intelligence (AI) can totally revolutionize this sector in near future. Since, work from human resource has time limitation; machines with artificial intelligence can be better utilized to overcome this lacuna. Further, farmer needs experts advise to produce good crop but they may not be available at all the time and decision-making ability changes from person to person which may lead to inadequate and indecorous decisions, this can be overcome by adopting Expert Systems (ES) in crop production. These technologies (AI/ES) can aid in providing information and supporting the decision-making for instance, crop condition, weather signaling challenges, nutrient and water management, crop protection and harvesting. As a result, they may positively contribute towards increasing yields or minimizing losses.

The primary aim of this review paper is to explore and illuminate the multifaceted applications and benefits of integrating artificial intelligence into the realms of irrigation and nutrient management in agriculture. By examining recent research, case studies, and innovative technologies, this review seeks to showcase how AI is revolutionizing the conventional paradigms of agricultural practices. The paper will delve into how AI-driven approaches are reshaping irrigation scheduling, soil moisture monitoring, fertilizer application, and precision agriculture techniques. Through comprehensive analysis, the review aims to provide insights into the tangible advantages that AI can bring to optimizing irrigation and nutrient management.

2. History of Artificial Intelligence (AI)

In the journey of artificial intelligence (AI), significant milestones have marked its evolution. It all began in 1950 with Alan Turing's pioneering paper pondering the concept of thinking machines. The subsequent years saw remarkable progress: in 1951, Christopher Strachey and Dietrich Prinz developed game AI programs for checkers and chess, respectively. Then, in 1956, John McCarthy coined the term "Artificial Intelligence" during the Dartmouth conference, shaping the field's identity. MIT established the first AI Laboratory in 1959, while 1960 witnessed the integration of AI into industry with General Motors' assembly line robot. The year 1961 brought the first chatbot, ELIZA, showcasing early human-computer interaction. Advancing into the late 20th century, IBM's Deep Blue defeated chess champion Garry Kasparov in 1997, highlighting AI's prowess in complex games. The year 2005 witnessed the autonomous victory of Stanford Racing Team's car, Stanley, in the DARPA Grand Challenge, emphasizing progress in self-driving technology. The pinnacle came in 2011 as IBM's Watson triumphed over Jeopardy! champions, illustrating AI's capacity in natural language understanding and knowledge retrieval. These milestones collectively define AI's remarkable journey from theoretical speculation to practical application across diverse domains.

3. Artificial Intelligence Techniques in Agriculture

Artificial Intelligence (AI) techniques have gained significant attention in the agricultural sector due to their potential to transform traditional farming practices into smart, data-driven, and efficient systems. These techniques encompass a range of methodologies and technologies that leverage data analysis, machine learning, remote sensing, and automation to optimize various aspects of agriculture. The integration of AI into agriculture holds promise for addressing challenges related to resource efficiency, productivity, and sustainability.

3.1 Machine learning algorithms

Machine learning algorithms are at the forefront of AI-driven agricultural advancements. These algorithms enable computers to learn from data patterns and make predictions or decisions without being explicitly programmed. In agriculture, machine learning techniques are employed for tasks such as yield prediction, disease detection, and pest management. Algorithms like decision trees, random forests, support vector machines, and neural networks can analyze historical data to make informed decisions about planting, harvesting, and crop protection.

3.2 Remote sensing and imaging

Remote sensing technologies, including satellites, drones, and sensors, provide a wealth of data that can be harnessed to monitor crop health, soil conditions, and water availability. AI algorithms analyze satellite imagery, multispectral data, and thermal imagery to detect anomalies, stress, and disease outbreaks in crops. This real-time monitoring enhances precision agriculture by enabling farmers to take timely actions to mitigate issues and optimize resource allocation Chlingaryan *et al.* (2018). .

3.3 Data analytics and big data

The agricultural sector generates vast amounts of data related to weather conditions, soil properties, crop growth, and more. AI-driven data analytics can process this data to extract insights and patterns that aid decision-making. Big data techniques facilitate the identification of correlations between various factors, leading to optimized irrigation schedules, improved nutrient management, and enhanced crop yield (Schut and Giller (2020)).

3.4 Precision agriculture

Precision agriculture involves tailoring agricultural practices to the specific needs of each portion of a field, rather than treating the entire field uniformly. AI technologies play a pivotal role in precision agriculture by integrating data from various sources—such as soil sensors, weather forecasts, and historical crop data—to create detailed field maps. These maps guide variable-rate application of irrigation, fertilizers, and pesticides, optimizing resource use and minimizing waste.

3.5 Deep learning and neural networks

Deep learning, a subset of machine learning, employs neural networks to analyze complex patterns in large datasets. In agriculture, deep learning models can process images of crops and soil to identify diseases, pests, and nutrient deficiencies. This technology enables early detection and targeted interventions, thereby reducing the need for broad-spectrum treatments processes (Thompson *et al.* (2015)).

3.6 Predictive modeling:

Predictive modeling uses historical data to make predictions about future outcomes. In agriculture, these models can forecast crop yields, soil moisture levels, and disease outbreaks. By integrating AI-driven predictive models into irrigation and nutrient management strategies, farmers can make informed decisions to maximize crop production while minimizing inputs.

4. Optimizing irrigation and nutrient management through artificial intelligence:

Effective nutrient management and precise irrigation are crucial elements for achieving sustainable and productive agriculture. Artificial Intelligence (AI) offers innovative solutions to address the challenges of resource optimization, crop health, and environmental impact in both areas. By harnessing AI techniques, farmers can enhance their irrigation and nutrient management practices, leading to improved yields, reduced resource wastage, and minimized environmental footprint.

4.1 Precision Irrigation: AI-driven precision irrigation aims to provide crops with the right amount of water at the right time and in the right location. By integrating data from weather forecasts, soil moisture sensors, and crop requirements, AI algorithms create customized irrigation schedules. This approach prevents over-irrigation, minimizes water loss due to evaporation and runoff, and ensures that water is directed where it's most needed.

Talaviya *et al.* (2020) reviewed the summary of irrigation automation which was done by different authors using various AI technologies.

Zubaidi *et al.* (2019) evaluated the performance of IoT (Internet of Things) based integrated expert water management (IEWM) system. The results (Table 1) revealed that IEWM system recorded higher accuracy (98.7 %) as compared to traditional water management system (87 %). Since, IEWM system is an artificial intelligence based expert system which is integrated with IoT sensors. Mainly because of this it’s having a high level of human intelligence and expertise which will overcome various complicate issues with the help of applications within the system and works like human experts but respond very quickly as compared to human experts. This IEWS is used for water management at farmland and water tank level which can also be used to alert various abnormal conditions identified in various applications.

Table 1: Kernel yield, Stover yield and harvest index of maize as influenced by sensor-based irrigation management

Treatment	Kernel yield (kg ha^{-1})	Stover yield (kg ha^{-1})	Harvest Index (H.I)
T_1 : Surface irrigation	6551	8007	0.45
T_2 : Drip irrigation at 3 days interval	8331	9485	0.47
T_3 : Green SMI based drip irrigation	10441	11975	0.47
T_4 : Yellow SMI based drip irrigation	7548	9145	0.45
T_5 : Sensor based drip irrigation at 25% DASM	10676	12273	0.47
T_6 : Sensor based drip irrigation at 50% DASM	8436	9690	0.46
T_7 : Sensor based drip irrigation at 75% DASM	6555	8033	0.45
S.Em.±	421	810	-
CD (p=0.05 or 0.01)	1299	2498	-

Chaitra (2020) reported that growth and yield of maize are drastically affected by moisture stress. In the present table also kernel yield was influenced by different levels of irrigation scheduling. The higher kernel yield observed in sensor-based drip irrigation at 25% DASM, because it maintained adequate availability of moisture throughout the crop growth period in turn it might have helped in good uptake of nutrients and favored on yield contributing factors.

4.2 Dynamic Nutrient Management: AI algorithms can optimize nutrient application by analyzing factors such as soil nutrient levels, crop type, growth stage, and weather conditions. This data-driven approach enables farmers to apply fertilizers precisely when and where they are needed, reducing the risk of nutrient imbalances, improving crop uptake, and minimizing environmental pollution from excess fertilizers.

Timsina *et al.* (2021) assessed nutrient management strategies for cereals, examining nutrient use efficiency (NUE) and utilizing the Nutrient Expert (NE) decision support system. The study considered factors like nutrient balance and utilized the RF algorithm. Notably, NUE in rice and P and K uptake in wheat and maize were pivotal contributors to grain yield.

Suchithra and Pai (2020) developed a system that harnessed soil test data to effectively classify and predict soil fertility indices and pH values based on diverse soil characteristics. Employing the Extreme Learning Machine (ELM) algorithm, known for its proficiency in classification and prediction, the research utilized a single hidden layer feedforward neural network (NN) structure. Impressively, the study achieved notable results, reporting accuracy rates of up to 78% for potassium fertility index prediction and up to 89% for pH value classification. Notably, the GRB activation function within the neural network demonstrated superior performance, showcasing its significance in optimizing accurate soil characteristic classification.

Coulibali et al. 2022 conducted a study in eastern Canada, comparing machine learning, probabilistic, and site-specific predictive models for effective potato crop fertilization. Their research aimed to determine NPK requirements, accounting for intricate factors such as soil, land management, and weather conditions, in order to achieve optimal yield and quality for potato (*Solanum tuberosum* L.) cultivation. The study addressed challenges in predicting nutrient levels due to the complexity arising from various variables, including genotypes, pests, and diseases. By evaluating different modeling approaches, the researchers sought to enhance fertilization strategies and support decision-making processes for potato farmers in the region.

Divya *et al.* (2013) in Bengaluru developed an automated robot for seeding and fertilization operation. From the tests conducted, it is evidently noted that the prototype works best for dry clayish (fine) soil where the seeding accuracy obtained was 94.827% with a machine speed of 55 revolutions per minute (rpm) as compared to seeding on a perfect flat surface (100 % seeding accuracy and 58- 60 rpm machine speed). The seeding accuracy obtained for sandy (medium coarse) soil is 82.75% with a machine speed of 48 rpm. Whereas, the seeding accuracy obtained for very coarse soil is 72.41% with a machine speed of 42 rpm.

Yu *et al.* (2018) utilized a deep learning-based model, including a fully connected neural network (FNN) and stacked autoencoders (SAE), to quantify canola leaf nitrogen concentration.

SAE inferred deep spectral features from hyperspectral images, improving nitrogen estimation accuracy.

4.3 Data integration and analysis: AI techniques excel at processing large datasets and extracting meaningful patterns. By integrating data from various sources, such as satellite imagery, soil sensors, and historical records, AI systems can create comprehensive profiles of fields and crops. This data-driven analysis guides decision-making for both irrigation and nutrient management, leading to more informed and accurate practices.

In the research conducted by Ghosal *et al.* (2018), they manually identified and gathered individual soybean leaves displaying various deficiency symptoms like potassium and iron. This was achieved through a destructive sampling process conducted in the field. The collection process involved the use of a digital camera to record the leaves and accompanying charts, with a total of 25,000 images being amassed. These images were meticulously labeled to establish a comprehensive dataset of soybean leaf images.

Support vector feature selection (SVFS), as a variant of SVM, showed great potential in selecting relevant features for nutritional deficiencies. Images of the top three leaves of a rice plant (*Oryza sativa* L.) and associated leaf sheaths were acquired using static scanning techniques. Thirty-two spectral and shape features were identified from these images by fusion of an RGB mean function and a Matlab region-prop function. NPK deficiencies were effectively detected using hierarchical identification. The overall accuracy of NPK deficiencies for the four growth stages was 86.15, 87.69, 90.00, and 89.23%, respectively. Validation was performed with data from different years, and the accuracies were 83.08, 83.08, 89.23, and 90.77%, respectively (Chen *et al.* (2014)).

4.4 Predictive modeling for nutrient needs: AI-driven predictive models can forecast a crop's nutrient requirements based on growth stages, historical data, and environmental conditions. By anticipating nutrient demands, farmers can adjust their fertilization strategies accordingly, optimizing crop growth and minimizing excess nutrient application.

Abioye *et al.* (2022) have exemplified the successful application of ML in various realms, Machine Learning (ML) is a dynamic approach that amalgamates mathematical modeling with intricate algorithms to execute tasks by leveraging insights from available data.

This versatile technique has demonstrated efficacy across diverse domains necessitating functions like classification, prediction, and recommendations. Showcasing its potential to enhance decision-making and problem-solving processes through its adaptive learning mechanisms.

Tewari *et al.* (2020) designed a real-time variable-rate chemical spraying system in West Bengal for precise agrochemical application on diseased paddy crops. The system utilized web cameras, a laptop for image processing, microcontrollers, and solenoid valve-equipped nozzles for spraying. Chromatic aberration-based image segmentation identified diseased regions, while disease severity guided solenoid valve timing to ensure accurate agrochemical amounts. Functional diagrams were provided for system operation

Kouadio *et al*. (2018) explored the application of Extreme Learning Machines (ELM) for analyzing soil fertility parameters and yield prediction. ELM-based models were tested with various combinations of predictor variables derived from soil organic matter (SOM), accessible exchangeable nutrients, and pH. The study compared ELM's outcomes with those of established techniques like Multiple Linear Regression (MLR) and Random Forest (RF). The researchers highlighted ELM's distinct value in selecting critical soil parameters to predict coffee yields, emphasizing its potential significance for advancing agricultural practices.

Backhaus *et al.* (2011) examined the robustness of supervised approaches in predicting plant nutritional status through classification models. Their study specifically evaluated the models' ability to handle substantial data sets containing variables like leaf age and pixel position in the leaf, which exhibit significant variance.

Conclusion

The integration of AI into irrigation and nutrient management marks a pivotal juncture in modern agriculture. AI's dynamic decision-making, predictive modeling, and real-time data analysis have revolutionized these practices. The synergy yields precision irrigation conserving water and bolstering yields, and adaptive nutrient management curbing waste. Despite challenges, AI's potential to enhance efficiency, productivity, and sustainability in agriculture is undeniable. As AI progresses, the path towards resilient agricultural systems becomes clearer, promising a brighter future for food security and environmental preservation.

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