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Artificial Intelligence in Agricultural Water Management Research: Literature Review and Research Agenda

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Abstract— *Artificial intelligence (AI) enhances agricultural water management by enabling precise, efficient, and sustainable irrigation practices. With rising water scarcity and the demand for increased productivity in agriculture, AI-powered applications provide innovative approaches for irrigation scheduling, water use efficiency, and decision support. This study investigates the use of AI in agricultural water management, concentrating on methodology, applications, and advantages. Different case studies and developing algorithms are also discussed to provide a detailed understanding of AI- AI-transformative methods. The case studies show that incorporating AI into agricultural water management promotes sustainable practices by reducing water use and environmental effects. This proactive approach saves water, increases water use efficiency, and provides real-time monitoring of the main components of agricultural water management, contributing to sustainable irrigation and farming developments. Eventually, developing an AI-ANN model to assess the complex nonlinear relationships in water balance is essential for the large-scale assessment.*

Keywords— ***Artificial Intelligence, Neural Network, Agricultural Water Management, Precision Agriculture, Water Use Efficiency.***

I. INTRODUCTION

Water scarcity is one of the most critical challenges in agriculture worldwide. Water is a crucial resource for agriculture, accounting for almost 70% of global freshwater consumption (FAO, 2020). Efficient water management is critical for addressing water scarcity, climate change, and increasing food demand. Growing populations (UN, 2022) and climate change (IPCC, 2021) contribute to rising food demand, necessitating efficient water management measures. Traditional water management strategies, which are frequently based on fixed schedules and empirical approaches, do not take into account changing environmental conditions or different crop requirements. This leads to failure in optimizing water consumption, resulting in significant waste and decreased agricultural output (Ye et al., 2024). Emerging technologies such as artificial intelligence (AI) were developed as transformative solutions to address such challenges. Artificial intelligence (AI) is the development of human intelligence in machines, allowing them to acquire knowledge, analyze information, and solve problems (Collins et al., 2021). AI in agricultural water management includes machine learning (ML), deep learning (DL), computer vision, and predictive analytics, among other techniques (Elshaikh et al., 2024). These technologies use big data from many sources, such as remote sensing, Internet of Things (IoT) devices, and meteorological data, to deliver actionable insights to farmers and decision-makers (Benos et al., 2021).

AI is revolutionizing traditional agricultural water management techniques through precision irrigation, real-time monitoring, and predictive modeling (Ashoka et al., 2024). AI models, such as artificial neural networks (ANNs) and support vector machines (SVMs), have demonstrated high accuracy in predicting ET under varying climatic and soil conditions (Hameed et al., 2021). Precision irrigation systems powered by artificial intelligence evaluate data from soil moisture sensors, weather forecasts, and crop growth stages to supply the exact quantity of water at the right time, minimizing waste (Bhardwaj & Sharma 2024). Furthermore, AI-driven decision support systems (DSS) integrate multiple data sources, including soil qualities, crop characteristics, and weather patterns, to deliver specific irrigation recommendations based on crop water requirements (Ikudayisi et al., 2022). Paired with AI algorithms, remote sensing technology processes satellites to monitor field conditions, diagnose water stress, and improve water distribution (Chen et al., 2022). AI-driven solutions could identify leaks and inefficiencies in irrigation networks, assuring optimal water distribution while decreasing energy use (Türkler et al., 2023).

The use of artificial intelligence in agricultural water management shows enormous promise, but it confronts multiple challenges, including limited access to quality data, high implementation costs, and a lack of technical understanding among farmers (Odume, 2024). The availability of high-quality, accurate data and the complexity of AI models is a considerable challenge, especially in locations with limited infrastructure (William et al., 2023; Kumar 2019). Addressing such challenges needs joint efforts by researchers, policymakers, and technology providers to build user-friendly, cost-effective, and scalable solutions (Aldoseri et al., 2023). Eventually, farmers and policymakers can manage water scarcity issues, improve resource efficiency, and adjust to changing climate conditions by leveraging AI. This study intends to investigate the role of AI in agricultural water management, highlighting its methodology, applications, benefits, and limitations. The study examines case studies and current trends to provide insights into AI's transformative potential in alleviating water scarcity while promoting sustainable agriculture practices.

1. Types of Artificial Neural Networks (ANNs):

Artificial Neural Networks (ANNs) play an important role in water management by tackling difficulties, such as resource optimization, distribution, and conservation. Different varieties of ANNs are used depending on the specific needs of water-related tasks. The following are the types of ANNs widely employed in water management, as well as their applications:

- *Feedforward Neural Networks (FNNs)*: A feedforward neural network is an artificial neural network in which the connections between the nodes (neurons) do not follow a cycle, as shown in Fig. 1. The information flows in one direction from the input layer to the hidden levels, and then to the output layer (Zhang & Xu, 2023; Ghosh, 2024). The FNNs are suitable for activities that need simple forecasts or classifications, such as calculating water demand or forecasting reservoir levels. It has been utilized to forecast daily water consumption in urban areas using historical usage and weather data (Yu et al., 2020).
- *Convolutional Neural Networks (CNNs)*: It is a deep learning method designed specifically for visual data analysis. CNNs are designed for spatial data processing with convolutional layers extracting features from images and pooling layers reducing dimensionality, as shown in Fig. 2. CNNs are widely used to process images (Yamashita et al., 2018), particularly in analyzing satellite imagery and geographic data in water resource management (Charan et al., 2020). CNNs have been also utilized for water classification and better accuracy compared to state-of-the-art methods (Asghar et al., 2023), and are also used for water quality prediction (Vijay et al., 2024).

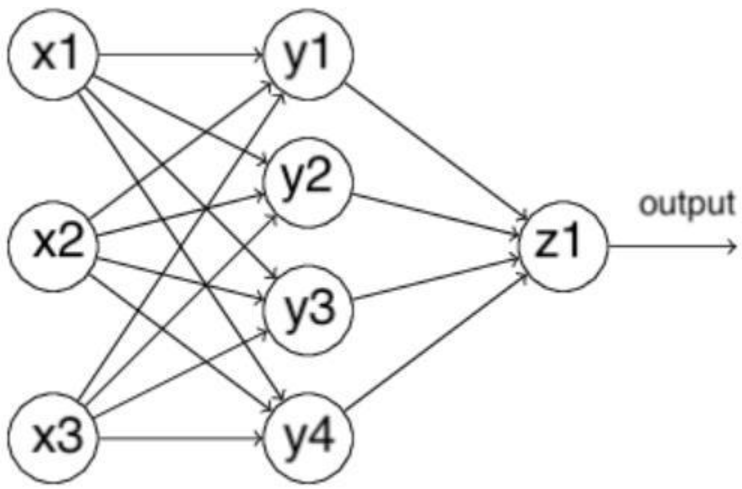

Fig.1. Illustration of a simple Feedforward Neural Network (HU, 2020)

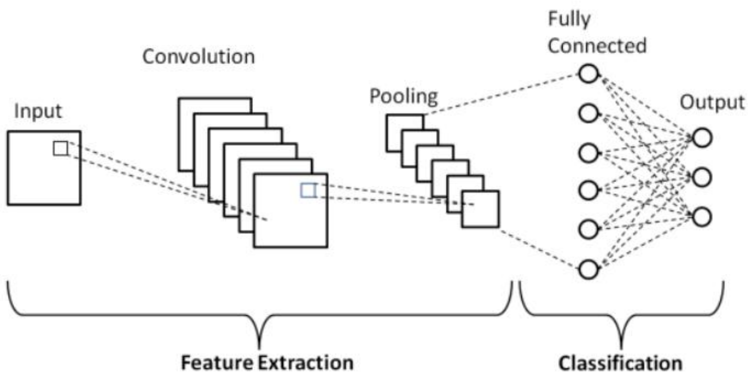

Fig.2. Illustration of a simple Convolutional Neural Network (Phung & Rhee, 2019)

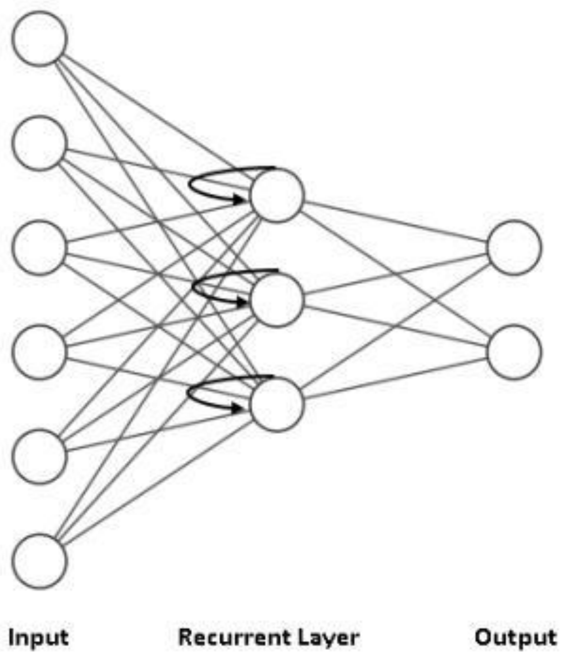

Fig.3. Illustration of a simple Recurrent Neural Network (Khan et al., 2021)

- *Recurrent Neural Networks (RNNs)*: Recurrent Neural Networks are a type of artificial neural network that is widely utilized for sequential data processing. RNNs handle data in numerous time steps, as opposed to feedforward neural networks, which do it in a single pass, as shown in Fig. 3. RNNs are suitable for sequential data processing, such as time-series estimates of water flow in rivers and reservoirs (Park et al., 2020).

- *Long Short-Term Memory Networks (LSTMs):* LSTMs are a kind of deep neural network that is intended to capture historical information from time series data and can forecast long-term nonlinear trends, as shown in Fig. 4. LSTMs are effective for addressing long-term dependencies in water-related time series data, such as drought prediction (Zhang et al., 2020), rainfall-runoff modeling (Kratzert et al., 2018), and groundwater level prediction (Nazari et al., 2024).

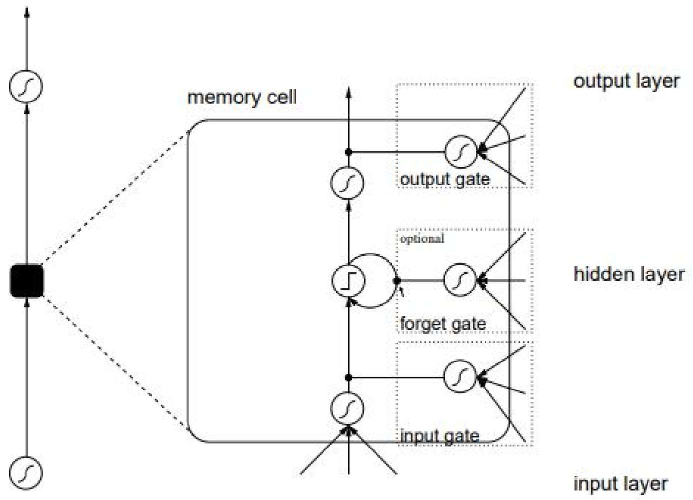

Fig.4. Illustration of a simple Long Short-Term Memory Network (Staudemeyer & Omlin 2013)

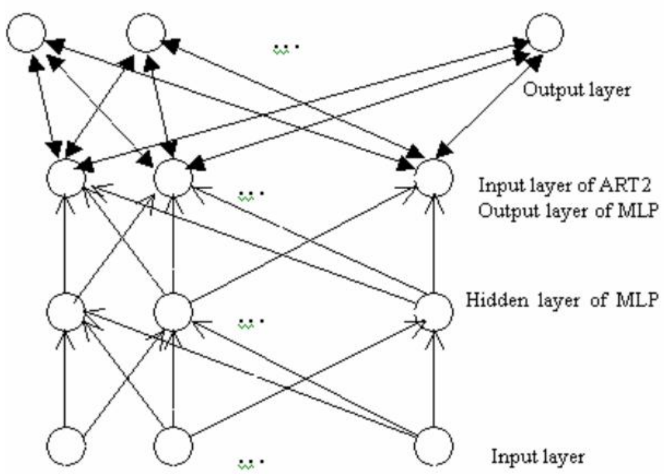

Fig.5. Illustration of a simple Hybrid Network (Gavrilov et al., 2006)

- *Hybrid Networks:* A hybrid network is the linking of two or more basic networks, each with its own set of nodes, as shown in Fig. 5. For complex tasks like flood modeling, a hybrid network has been integrated with several types of networks, such as CNNs and RNN (Li et al., 2024). A hybrid artificial neural network (ANN) model was also developed to simulate future stream flows (Mugume et al., 2024).

Deep Neural Networks (DNNs): It has many hidden layers, and if the layers are more than 3 layers, including the output and input layers, then it is called a deep neural network, as shown in Fig. 6. DNNs are widely utilized in agricultural water management, such as crop water requirement estimation (Elbeltagi et al., 2020), soil moisture prediction and monitoring (Wang et al., 2024), irrigation scheduling optimization (Yang et al., 2020), drought prediction and monitoring (Kaur et al., 2020), crop yield prediction (Khaki & Wang, 2019), water distribution (Lazarovitch et al., 2009), and irrigation water requirements (Mokhtar et al., 2023).

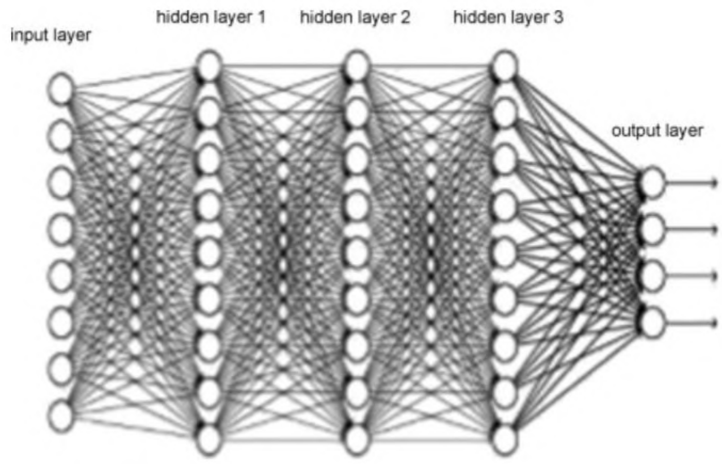

Fig.6. Illustration of a simple Deep Neural Network (Mohanasundaram et al., 2019)

2. **Application of AI in Agricultural Water Management:**

Several models/algorithms have been applied to enhance agricultural water management through AI, including:

- *Smart Irrigation*: AI combines data from soil sensors, weather forecasts, and crop growth phases to determine accurate water requirements. This minimizes over-irrigation and assures optimal water use through machine-learning algorithms that can estimate crop evapotranspiration rates using historical meteorological data (Goap et al., 2018; Younes et al., 2024).
- *Predictive Modeling/algorithms*: Predictive algorithms powered by AI estimate future water requirements based on environmental conditions, helping farmers and policymakers plan more effective irrigation systems. This reduces the risk of water scarcity and unexpected droughts, making the irrigation system more adaptable to climate unpredictability (Kim et al., 2023; Kavya et al., 2023).
- *Real-Time Monitoring*: AI uses data from IoT devices and remote sensing technologies to monitor real-time soil moisture, evapotranspiration, and crop health, enabling better management. This integration allows monitoring areas that are difficult to access manually (large-scale levels), allowing for more targeted actions and lowering the need for excessive irrigation (Cardoso et al., 2020; Chandrappa et al., 2023).
- *Decision Support Systems (DSS)*: AI systems can include data such as soil type, weather, and crop requirements to provide straightforward suggestions for the best water management practices (Vianny et al., 2022; Morain et al., 2024).
- *Leak Detection and Network Optimization*: AI-based solutions can detect leaks and inefficiencies in irrigation networks, assuring uniform water distribution and reducing

losses (Tylman et al., 2010; Türkler et al., 2023).

- *Adapting to Climate Changes*: AI contributes to the adaptation of water management policies to climate variability and extreme weather events by assessing long-term patterns and recommending mitigating measures (Filho et al., 2022; Lewis et al., 2024).

II. FUTURE TREND AND PROPOSED AGENDA

Water balance includes various interconnected processes, including precipitation, evaporation, infiltration, deep percolation, and runoff, all affected by complicated elements, such as land use (i.e., cropping patterns and field heterogeneity), soil characteristics, and climatic conditions. AI-powered algorithms have the potential to capture complex interactions among variables, mainly due to the flexibility to model nonlinear relationships (Liu & Lei, 2022). Further, the application of ANN for water balance can be done using remote sensing without intensive collected data (Karahan et al., 2024; Saha & Pal, 2024). Another problem is that water balancing mechanisms function across several spatial and temporal dimensions, ranging from small catchments to extensive river basins and from brief daily intervals to prolonged annual cycles (Dean et al., 2016). Utilizing Artificial Intelligence (AI), specifically Artificial Neural Networks (ANNs), to assess water balance presents numerous promises for the precise assessment of large-scale levels of agricultural water management (Venitsianov & Skonechnii, 2021). Eventually, artificial neural networks (ANNs) have the promising potential to model complex nonlinear relationships in estimating water balance at the large-scale level.

III. CONCLUSIONS

Agricultural water management is often complex, several indicators have to be considered in the analysis, such as weather data, crop water demands, leaching requirements, and soil characteristics. Several AI algorithms have emerged, such as Recurrent Neural Networks (RNNs), Feedforward Neural Networks (FNNs), Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and Hybrid Models. The integration between these AI-powered tools and IoT devices has the potential to enhance real-time monitoring and decision-making. By developing the relevant algorithms and choosing the appropriate AI method, innovative solutions to address water scarcity and improve water use efficiency can be achieved. Further, AI can achieve sustainable agricultural water management while conserving vital water resources through accurate drought and rainfall pattern predictions. Eventually, artificial neural networks (ANNs) possess considerable potential for estimating complex nonlinear relationships in water management, including water balance, and for tackling prevalent challenges such as data quality issues, the complexity of hydrological processes, model interpretability, and scale-related concerns (spatiotemporal resolution).

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