DESIGNING AND DEVELOPING A SMART CROP IRRIGATION SCHEDULING SYSTEM USING MACHINE LEARNING IN ZAMBIA

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A Report submitted to the Zambia University College of Technology in partial fulfilment for the award of the Degree in Cyber Security.

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List of Acronyms

AI: Artificial Intelligence

CART: Classification and Regression Trees

ETc: Crop Evapotranspiration

IoT: Internet of Things

SLA: Service Level Agreement

Chapter One: Introduction

1.1. Introduction

In many parts of the world, agriculture forms the bedrock of economies by ensuring food security and generating employment. Although Zambia represents only a modest focus in this study, its water management challenges echo a global crisis—agriculture consumes approximately 70% of the world's freshwater resources [1]. Traditional irrigation practices, which are still prevalent in many regions, are fraught with inefficiencies. Over-irrigation leads to soil saturation, resulting in nutrient leaching and increased water runoff, while under-irrigation stresses crop and diminishes yield quality [2]. These shortcomings are further exacerbated by the unpredictable impacts of climate change—such as prolonged droughts and erratic rainfall—that undermine sustainable agricultural productivity [3]. Furthermore, the advent of artificial intelligence (AI) offers a transformative solution to these longstanding challenges. AI-driven technologies, particularly the Classification and Regression Trees (CART) algorithm, are revolutionizing irrigation scheduling by processing complex, non-linear environmental data. These models analyse historical weather patterns and soil moisture data to predict optimal irrigation schedules tailored to diverse crop types [4]. By dynamically adjusting irrigation based on real-time data, these systems can enhance water use efficiency—improving usage by up to 15% and boosting crop yields by 11% compared to conventional methods [5]. CART's ability to handle both numerical and categorical data makes it particularly suitable for processing diverse agricultural inputs while maintaining computational efficiency.

This research proposes the design and development of a machine learning-based crop irrigation scheduling system using the CART algorithm. The system is driven by three primary objectives: (1) to analyse historical weather and soil moisture data for predicting optimal irrigation schedules; (2) to provide real-time watering recommendations based on current environmental conditions; and (3) to integrate a user-friendly interface that empowers farmers to input crop details and receive AI-generated irrigation schedules. Although the system draws on insights from Zambia, its underlying principles and methodologies are broadly applicable to agricultural regions worldwide, offering scalable solutions to the challenges of water scarcity and inefficient irrigation.

Through this integrated approach, the proposed system aims not only to optimize water management but also to support sustainable agricultural practices and enhance food security in an era defined by climate change and resource limitations [6].

1.2. Background

Agriculture, as a critical driver of global and local economies, is increasingly under pressure due to the dual challenges of growing population demands and environmental constraints [7]. In Zambia and other regions worldwide, traditional irrigation methods remain the norm, yet they are often plagued by significant inefficiencies. Surface irrigation, the most common method, suffers from limited control over water distribution; farmers typically rely on visual assessments—such as observing leaf color and curling—to decide when to irrigate [8], [9]. This approach, while rooted in generations of practical experience, often results in either over-irrigation or under-irrigation. Over-irrigation saturates the soil, leading to nutrient leaching and excessive runoff, whereas under-irrigation stresses crops, thereby reducing yield quality and overall productivity [10]. Further compounding these issues are the unpredictable impacts of climate change. Prolonged droughts, erratic rainfall, and rising temperatures have made water availability even more uncertain, intensifying the need for adaptive water management strategies [11]. Traditional methods struggle to cope with these fluctuations, necessitating the development of more precise, data-driven approaches. Recent advances in remote sensing, Internet of Things (IoT) technologies, and real-time data acquisition have paved the way for precision irrigation systems that can dynamically adjust watering schedules based on current environmental conditions [1].

Model-based approaches in irrigation scheduling often focus on estimating crop evapotranspiration (ETc) and predicting soil water balance, while monitoring-based approaches leverage real-time data from soil moisture sensors and crop health indicators [12]. Despite these innovations, challenges persist due to uncertainties in weather forecasts and the labor-intensive nature of conventional monitoring methods [13]. Integrating real-time weather forecasts—particularly short-term rainfall predictions—has shown promise in enhancing the precision of these models, though forecast uncertainties can sometimes lead to unplanned irrigation events [14]. Against this backdrop, artificial intelligence (AI) emerges as a transformative solution. Machine learning models, especially those based on decision trees, are uniquely suited to analyse complex, non-linear relationships among various environmental factors [15]. By processing historical weather patterns and soil moisture data, AI-driven systems can predict optimal irrigation schedules tailored to specific crop types. This not only improves water use efficiency—by up to 15% in some studies—but also increases crop yields by as much as 11% compared to traditional methods [16]. The seamless integration of these technologies with IoT and data analytics marks a significant step forward in achieving sustainable water management in agriculture.

1.3. Problem Statement

Agriculture faces critical water management challenges owing to outdated irrigation practices that often lead to inefficient water usage [17]. Traditional, experience-based methods typically result in either over-irrigation—causing nutrient leaching and runoff—or under-irrigation, which stresses crops and diminishes yields. These inefficiencies are further exacerbated by climate-induced phenomena such as prolonged droughts and erratic rainfall [18]. Despite agriculture's substantial share of global freshwater consumption, current practices fail to deliver water optimally to crop root zones. This study proposes a machine learning–driven irrigation scheduling system that integrates historical and real-time environmental data to generate precise, adaptive watering recommendations. By shifting from heuristic to data-driven decision-making, the proposed approach aims to enhance water use efficiency and foster sustainable agricultural practices.

1.4. Research Objectives

1. To analyse historical weather and soil moisture data using decision trees to optimize irrigation schedules for various crops.
2. To create a real-time irrigation recommendation system based on environmental conditions to enhance water efficiency.
3. To provide an intuitive interface enabling farmers to input crop details and receive AI-generated irrigation schedules.

1.5. Research Questions

1. How can historical weather patterns and soil moisture data be analysed using decision trees to predict the optimal irrigation schedule for different crop types?

2. How can real-time environmental conditions be utilized to provide watering recommendations that ensure efficient water usage?

3. How can a user-friendly interface be developed that allows farmers to input crop details and receive AI-generated irrigation schedules?

1.6. Scope of the Study

This project entails the design and development of an intelligent crop irrigation scheduling system, driven by machine learning techniques, with a primary focus on the Classification and Regression Trees (CART) algorithm. The system is structured around three core components: (1) a historical data analysis module, (2) a predictive irrigation scheduling engine, and (3) a real-time recommendation feature.

The historical data module will ingest and analyze extensive datasets, including weather parameters (precipitation, temperature, evapotranspiration) and soil moisture levels, to identify key temporal correlations for model training. The prediction engine, powered by CART, will generate optimal irrigation schedules tailored to specific crop types—detailing the timing, frequency, and duration of irrigation events to maximize water-use efficiency and crop yield. The real-time recommendation system will dynamically adjust schedules based on live inputs from weather APIs and IoT soil sensors, enabling context-aware irrigation guidance.

A simplified, user-friendly interface will allow farmers to input key parameters such as crop type and field location, and receive AI-generated schedules and actionable recommendations. The system architecture is centered entirely on the CART algorithm, with all data processing, decision modeling, and interface logic designed to support its use in precision irrigation.

Limitations of the project include:

1. Crop diversity is initially limited to common types; expanding to other crops will require additional data collection and validation.
2. Geographic generalization is constrained by available historical datasets, optimizing the model primarily for climatically similar regions.
3. The system is designed as a decision support tool and does not integrate or automate irrigation hardware control.

4. Performance is contingent on the quality and continuity of external weather and soil moisture data.
5. The scope is restricted to the CART algorithm, excluding exploration of other machine learning methods.
6. The user interface prioritizes simplicity and usability, omitting advanced features in the initial phase.
7. Real-world validation will be limited due to resource and time constraints, with initial testing based on simulations or limited field data.

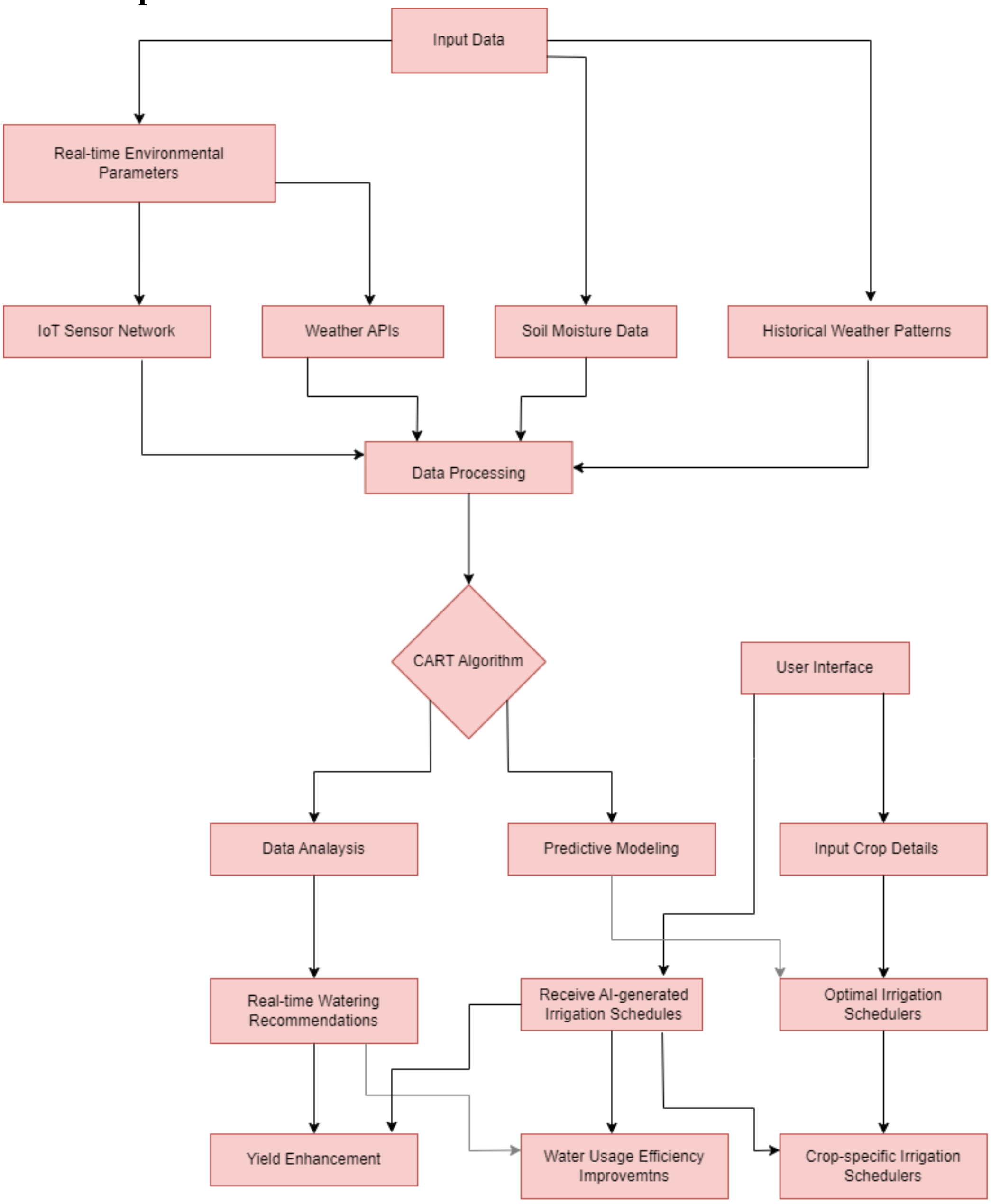
1.7. Significance of the Study

This research holds significant implications for the agricultural sector globally, particularly within the context of escalating water scarcity and the imperative for sustainable resource management. By addressing the inefficiencies inherent in traditional irrigation practices through the application of artificial intelligence and the CART algorithm, this study contributes to the development of data-driven solutions capable of optimizing water utilization and enhancing crop yields. This is crucial in an era defined by increasing global population and the unpredictable impacts of climate change, which collectively threaten food security and agricultural livelihoods.

The significance of this research is particularly pronounced for the African continent, where agriculture forms the backbone of many economies and a primary source of employment. African agricultural systems are often characterized by a heavy reliance on rain-fed agriculture and traditional irrigation methods, rendering them highly vulnerable to the vagaries of climate variability, including prolonged droughts and erratic rainfall. The proposed smart irrigation scheduling system offers a pathway towards greater resilience by providing farmers with precise, real-time watering recommendations tailored to specific crop needs and environmental conditions. This can lead to improved water use efficiency, reduced water wastage, and ultimately, enhanced agricultural productivity, contributing directly to poverty reduction and economic growth across the continent.

Specifically for Zambia, the focus country highlighted in this study, the development of such a system carries substantial weight. Agriculture is a critical sector in the Zambian economy, playing a vital role in food security and employment generation. The water management challenges faced by Zambia, as echoed globally, necessitate innovative solutions to ensure sustainable agricultural productivity. The proposed system, by leveraging historical and real-time data to optimize irrigation, has the potential to significantly improve water efficiency, mitigate the risks associated with climate change, and contribute to more stable and higher crop yields for Zambian farmers. Furthermore, the emphasis on a user-friendly interface ensures that the benefits of this advanced technology can be readily accessible to farmers with varying levels of technical expertise, fostering widespread adoption and maximizing the positive impact on Zambian agriculture and its contribution to national development.

1.8. Conceptual Framework



1.9. Summary

The first chapter of this proposal introduces a research project focused on designing a smart, machine learning-driven irrigation system. It highlights agriculture's global economic importance and the pressing issue of water scarcity, worsened by inefficient traditional irrigation. Experience-based methods lead to water waste, nutrient loss, and lower yields, problems amplified by climate change. Artificial intelligence, particularly the CART algorithm, is presented as a data-driven solution for optimization. The proposed system will analyze historical data, offer real-time irrigation advice, and include a farmer-friendly interface. Inspired by Zambian agriculture, the system targets global application as a CART-based decision support tool.

Chapter Two: Interim Literature Review

2.1. Introduction

Agriculture faces unprecedented challenges in water management, with traditional irrigation methods proving increasingly inadequate in the face of climate change and growing global food demands. The urgent need for precision water use has sparked significant interest in technological interventions, particularly machine learning and artificial intelligence. This literature review explores the evolving landscape of smart irrigation technologies, examining how advanced computational techniques are transforming agricultural water management, enhancing efficiency, and addressing critical challenges of crop water requirements and sustainable agricultural practices.

2.2. Related Works

Related seeks to bring out the related works done by researchers in various domains, illustrating the transformative impact of machine learning on traditional practices. The evolving landscape of technological interventions has spurred research across multiple sectors, as detailed below:

2.2.1. Machine Learning in Manufacturing Industries

In manufacturing, machine learning algorithms have been employed to optimize production processes and predict equipment failures. Predictive maintenance models reduce downtime and improve resource allocation by analyzing sensor data and historical performance metrics [19]. These studies underscore the potential of such models to streamline operations and reduce waste, resulting in measurable improvements in production efficiency and cost reduction [20].

2.2.2. Machine Learning in the Education Sector

The education sector has witnessed the integration of machine learning for personalized learning experiences and performance prediction. Algorithms that analyze student engagement, learning styles, and historical academic data help customize educational content and enhance learning outcomes [21]. Research indicates that these tailored approaches not only improve student performance but also enable early intervention for at-risk learners, thereby significantly contributing to overall educational quality [22].

2.2.3. Machine Learning in Agriculture

In agriculture, the application of machine learning focuses on precision irrigation and crop yield optimization. Decision tree-based models (e.g., CART) are utilized to process complex environmental data—including soil moisture and weather patterns—to predict optimal irrigation schedules [23]. This data-driven approach has been shown to enhance water use efficiency and crop productivity, thereby addressing the dual challenges of water scarcity and food security in a changing climate [24].

2.2.4. Machine Learning in Healthcare

Healthcare applications of machine learning illustrate its capacity to enhance diagnostic accuracy and personalize treatment protocols. Predictive models that analyze patient data can identify disease risk factors, optimize treatment strategies, and enable real-time health monitoring [25]. These methodologies not only contribute to improved clinical outcomes but also promote more efficient resource allocation in medical settings, highlighting the versatility and impact of machine learning across critical sectors [26].

2.2.5. Agricultural Water Management Technologies

Researchers have increasingly focused on developing precision irrigation technologies to address water scarcity and inefficient resource utilization [27], [28]. Early studies predominantly concentrated on traditional surface irrigation methods, which typically relied on farmers' empirical knowledge and visual crop assessments [29]. However, emerging research has shifted towards data-driven approaches that leverage advanced sensing and computational technologies.

2.2.6. Remote Sensing and IoT Integration

Significant advancements have been made in integrating Internet of Things (IoT) technologies and remote sensing techniques for agricultural monitoring [30]. These technologies enable real-time data collection of environmental parameters, providing unprecedented insights into crop water requirements and soil moisture dynamics. Researchers have demonstrated the potential of sensor networks to transform irrigation management by offering granular, time-sensitive information [31].

2.2.7. Machine Learning in Irrigation Scheduling

The application of machine learning algorithms in agricultural water management has emerged as a promising research direction [32]. Particularly, decision tree-based approaches like Classification and Regression Trees (CART) have shown remarkable potential in

processing complex, non-linear environmental data. Studies have highlighted the algorithm's ability to handle diverse agricultural inputs while maintaining computational efficiency [33].

2.2.8. Predictive Modeling Approaches

Researchers have developed various predictive models to optimize irrigation scheduling. These models range from traditional crop evapotranspiration estimation techniques to advanced machine learning frameworks [34], [35]. The integration of weather forecasts, soil moisture data, and crop-specific parameters has been a focal point of recent investigations [36].

2.2.9. Climate Change Adaptation Strategies

With increasing climate variability, research has emphasized the need for adaptive irrigation strategies [37]. Studies have explored how advanced computational techniques can help agriculture become more resilient to changing environmental conditions, particularly in regions experiencing prolonged droughts and erratic rainfall patterns [37].

2.2.10. User Interface and Technology Adoption

Recognizing the importance of farmer accessibility, researchers have also investigated user interface designs for agricultural decision support systems [38]. These studies emphasize the critical role of creating intuitive, user-friendly platforms that can translate complex AI-generated recommendations into actionable insights for farmers.

The related works in this domain demonstrate a clear trajectory towards more sophisticated, data-driven approaches in agricultural water management. However, significant opportunities remain for developing comprehensive, user-friendly systems that can provide precise, real-time irrigation recommendations across diverse agricultural contexts.

2.3. Review of the Related Works

2.3.1. Water Scarcity and Agricultural Challenges

Agriculture faces unprecedented water management challenges, with traditional irrigation methods demonstrating critical inefficiencies. The FAO revealed that agriculture consumes approximately 70% of global freshwater resources, yet surface irrigation techniques deliver only 30-50% of water effectively to crop root zones [39]. Empirical studies by Asmamaw et al., highlight that farmers' experience-based irrigation scheduling leads to significant water wastage, nutrient leaching, and reduced crop productivity [40]. The economic implications are substantial, with global agricultural water losses estimated at over $100 billion annually,

while environmental consequences include groundwater depletion and ecosystem disruption [41]. These challenges underscore the urgent need for technological interventions that can provide precise, data-driven irrigation management solutions to enhance water efficiency and agricultural sustainability.

2.3.2. Machine Learning in Agricultural Water Management

The evolution of data-driven irrigation approaches has transformed agricultural water management through advanced machine learning techniques. Arabelli et al., demonstrated that machine learning algorithms can significantly improve water use efficiency by processing complex environmental datasets, with predictive models showing potential water savings of 15-25% compared to traditional methods [42]. Comparative studies by Tamayo-Vera, Wang & Mesbah, revealed that different algorithms perform variably in agricultural contexts: neural networks excel in non-linear prediction, support vector machines provide robust classification, while decision trees offer superior interpretability and feature importance analysis [23]. Decision tree methodologies, particularly CART, have emerged as particularly promising, with Senapaty, Ray & Padhy, highlighting their unique ability to handle both numerical and categorical agricultural data while providing transparent, easily interpretable decision-making frameworks [43].

2.3.3. Classification and Regression Trees (CART) in Precision Agriculture

CART has emerged as a powerful machine learning technique in precision agriculture, offering unique capabilities for complex environmental data analysis. Mienye & Jere, established the theoretical foundations, demonstrating CART's ability to handle non-linear relationships and provide interpretable decision-making processes [44]. Comparative studies by Tantalaki, Souravlas & Roumeliotis, revealed CART's superior performance in agricultural datasets, particularly in handling mixed data types and producing transparent predictive models [45]. Araújo et al., highlighted CART's distinct advantages, showing it outperforms neural networks and support vector machines in agricultural applications by providing clear feature importance, lower computational complexity, and easier implementation in resource-constrained farming environments [46]. The algorithm's capacity to effectively segment and predict crop water requirements makes it particularly valuable for precision irrigation scheduling.

2.3.4. Predictive Modelling for Irrigation Scheduling

Existing predictive approaches for irrigation scheduling have evolved from simple crop evapotranspiration models to sophisticated machine learning techniques. Jamal et al., demonstrated that early models relied primarily on meteorological data, with limited accuracy in real-world agricultural settings [36]. Subsequent research by Shu et al., identified critical challenges in current prediction models, including difficulty in integrating multi-source environmental data and managing uncertainties in weather forecasts [47]. Sui & Vories, highlighted the complexity of developing accurate irrigation scheduling models, noting that existing approaches often struggle to account for site-specific variations in soil characteristics, crop types, and microclimate conditions [48]. The integration of comprehensive environmental datasets remains a significant challenge, with researchers emphasizing the need for more robust, adaptive predictive modelling approaches that can dynamically respond to complex agricultural ecosystems.

2.3.5. Real-Time Environmental Monitoring Technologies

The integration of Internet of Things (IoT) and sensor technologies has revolutionized agricultural monitoring capabilities. Olawade et al., demonstrated that advanced sensor networks can provide unprecedented granularity in environmental data collection, enabling near-instantaneous tracking of soil moisture, temperature, and crop health parameters [49]. However, Dave & Mittapally, identified significant data integration challenges, highlighting the complexity of harmonizing information from diverse sensors and platforms [50]. Real-time decision support systems have emerged as a critical solution, with Et-taibi et al., showing that integrated monitoring technologies can improve agricultural water management efficiency by up to 30%, providing farmers with actionable insights derived from continuous environmental data streams [51]. Despite technological advances, challenges remain in developing seamless, cost-effective, and user-friendly monitoring systems that can be widely adopted across different agricultural contexts.

2.3.6. User Interface Design in Agricultural Decision Support

Technological accessibility remains a critical barrier in agricultural decision support systems. Pandeya, Gyawali & Upadhaya, demonstrated that despite advanced technological capabilities, farmer adoption rates remain low due to complex, non-intuitive interfaces [52]. Research by Smidt & Okonya, identified significant challenges in technology adoption, particularly among small-scale and resource-constrained farmers, highlighting the need for context-specific, linguistically adaptable design approaches [53]. Patokar & Gohokar, proposed critical design principles for intuitive agricultural management tools, emphasizing simplicity, visual clarity, localized language support, and minimal cognitive load [54]. The most successful interfaces have been found to incorporate user-centric design elements such as straightforward data visualization, minimal technical jargon, and direct actionable recommendations that align with farmers' practical decision-making processes.

2.3.7. Climate Change and Adaptive Irrigation Strategies

Climate variability poses unprecedented challenges to agricultural water management. Kang, Khan & Ma, revealed that changing precipitation patterns and increasing temperature extremes are dramatically altering crop water requirements, with some regions experiencing up to 40% reduction in water availability [55]. Technological adaptations have emerged as critical solutions, with Sarma et al., demonstrating how advanced predictive models can provide resilient farming strategies that dynamically adjust to environmental changes [56]. Umutoni & Samadi, highlighted the importance of climate-responsive irrigation approaches, showing that machine learning-based systems can optimize water use by anticipating and mitigating climate-induced agricultural risks [57].

The comprehensive review of existing research underscores the critical need for innovative, technology-driven approaches to agricultural water management. By synthesizing insights from machine learning, IoT technologies, and adaptive modelling, this research aims to develop a comprehensive irrigation scheduling system that addresses the multifaceted challenges of water scarcity, technological accessibility, and climate resilience. The proposed research builds upon existing knowledge while targeting specific gaps in current technological solutions, particularly in providing precise, user-friendly, and adaptable irrigation management tools.

2.4. Proposed System

The escalating challenges of water scarcity and inefficient traditional irrigation methods in agriculture necessitate innovative solutions. This research proposes the design and development of a smart crop irrigation scheduling system leveraging machine learning, specifically the Classification and Regression Trees (CART) algorithm. The system aims to optimize water usage by analyzing historical weather and soil moisture data to predict tailored irrigation schedules for various crops. Furthermore, it will incorporate real-time environmental conditions to provide dynamic watering recommendations. A user-friendly interface will empower farmers to input crop details and receive actionable AI-generated irrigation guidance. This research, while drawing insights from Zambia, offers a globally applicable, data-driven approach to enhance water efficiency, promote sustainable agricultural practices, and improve food security in the face of climate change.

2.5. Summary

The literature review synthesizes existing research on the pressing challenges of water scarcity and the limitations of traditional irrigation in agriculture, exacerbated by climate change. It highlights the growing role of technological interventions, particularly machine learning and AI, in transforming water management practices. The review critically examines the integration of remote sensing and IoT for real-time data acquisition, the application of decision tree algorithms like CART for predictive modeling, and the evolution of irrigation scheduling approaches. Furthermore, it underscores the importance of user-friendly interfaces for facilitating technology adoption among farmers and the necessity of developing adaptive strategies to enhance agricultural resilience. Ultimately, the reviewed literature establishes the need for innovative, data-driven solutions, positioning the proposed research as a crucial step towards developing precise, accessible, and sustainable irrigation management systems.

Chapter Three: Methodology

3.1. Introduction

This chapter details the methodological framework adopted for the design and development of the proposed intelligent crop irrigation scheduling system. Employing an Agile Kanban software development methodology, this chapter underscores the iterative and collaborative principles guiding the project's execution. A central focus is the comprehensive requirements specification process, a critical stage for elucidating the system's intended functionalities and requisite quality attributes. This process commences with the identification of primary stakeholders, predominantly farmers, while also acknowledging the valuable contributions of researchers and potential investors. Subsequently, the chapter articulates the integrated approach to requirements elicitation, combining the breadth of data obtained through surveys and questionnaires with the depth of knowledge gleaned from a thorough review of existing literature and comparable systems. Finally, it introduces the analytical techniques employed for requirements processing, specifically categorization and prioritization, thereby establishing the groundwork for the subsequent phases of system development and validation.

3.2. Software Development Methodology

The development of the smart crop irrigation scheduling system will be guided by an Agile methodology, specifically adopting the Kanban framework. This choice is predicated on the inherent flexibility and iterative nature of Agile approaches, which are particularly well-suited for projects involving evolving requirements and the need for continuous feedback from stakeholders. Kanban, as a specific implementation of Agile, offers a visual workflow management system that emphasizes continuous flow, limiting work in progress (WIP), and focusing on delivering value incrementally.

The core principles of Kanban that will be applied to this project include visualizing the workflow, limiting WIP, managing flow, making policies explicit, implementing feedback loops, and improving collaboratively and experimentally. Visualizing the workflow will involve creating a Kanban board to track the progress of tasks through different stages, such as requirements gathering, analysis, design, development, testing, and deployment. Limiting WIP will ensure that the development team focuses on completing a smaller number of tasks at a time, thereby improving efficiency and reducing bottlenecks.

Managing flow will involve continuously monitoring the movement of tasks through the Kanban board and identifying areas for improvement to ensure a smooth and efficient development process. Making policies explicit will involve clearly defining the rules and guidelines for each stage of the workflow. Regular feedback loops will be established through stakeholder reviews and demonstrations to ensure the system aligns with the evolving needs and expectations of the farmers. Finally, the team will continuously strive for improvement by collaboratively analyzing the workflow and experimenting with changes to enhance productivity and the quality of the final product.

The adoption of Kanban will facilitate a responsive and adaptive development process, allowing for adjustments to be made based on feedback and changing priorities. This iterative approach will enable the early delivery of functional increments of the system, allowing stakeholders to provide valuable input throughout the development lifecycle and ensuring the final product effectively addresses their needs in the context of crop irrigation scheduling.

3.3. Requirements Specification

The requirements specification phase is a foundational step in the software development lifecycle, particularly within the Agile Kanban framework. It involves systematically identifying, documenting, analyzing, and validating the needs and expectations of the stakeholders for the smart crop irrigation scheduling system. This iterative process ensures that the development efforts are aligned with the desired outcomes and that the final product effectively addresses the challenges of efficient crop irrigation.

3.3.1 Identify the Stakeholders

Identifying the key stakeholders is crucial for understanding the diverse perspectives and needs related to the proposed system. For this project, the primary stakeholders are farmers and gardeners. They are the direct users who will interact with the system to obtain irrigation schedules and recommendations. Their needs and challenges related to current irrigation practices, their understanding of technology, and their specific crop requirements will be central to defining the system's functionality and usability.

Secondary stakeholders include agricultural researchers who possess expertise in crop water requirements, soil science, and the application of technology in agriculture. Their input can provide valuable insights into the scientific accuracy and effectiveness of the irrigation schedules generated by the system. Potential investors also represent a key stakeholder group, as their interest in the project's viability and scalability will influence its future development and deployment. While the primary focus of the requirements gathering will be on the needs of the farmers, the perspectives of researchers and investors will be considered to ensure the system is both scientifically sound and has the potential for broader impact and sustainability.

3.3.2 Requirements Gathering

To effectively gather the requirements for the smart crop irrigation scheduling system, a blended approach incorporating surveys/questionnaires and a review of existing systems/literature will be employed.

Surveys and Questionnaires: These will be distributed to a diverse group of farmers, representing various farm sizes, crop types, and levels of technological literacy. The surveys will aim to collect both quantitative and qualitative data, including:

i. Current irrigation methods and challenges faced.
ii. Specific crop types cultivated and their unique irrigation needs.
iii. Environmental data currently used for irrigation decisions (if any).
iv. Expectations and desired features of a smart irrigation scheduling system.
v. Preferences regarding user interface design and information presentation.
vi. Technical infrastructure and accessibility (e.g., internet connectivity, smartphone usage).

Review of Existing Systems and Literature: A comprehensive review of existing smart irrigation systems, both commercial and research-based, will be conducted. This analysis will focus on:

i. Identifying common and effective features and functionalities.
ii. Understanding the technologies and algorithms currently employed.
iii. Analyzing user interfaces and user experience design.
iv. Identifying limitations and areas for potential improvement.

Furthermore, relevant academic literature on precision agriculture, irrigation scheduling, machine learning applications in agriculture, and the CART algorithm will be reviewed to establish a strong theoretical foundation and identify best practices in the field.

3.3.3 Requirements Analysis

The data gathered from the surveys/questionnaires and the review of existing systems/literature will be subjected to a thorough analysis process. This will primarily involve categorization and prioritization of the identified requirements.

Categorization: The requirements will be classified into two main categories:

i. **Functional Requirements:** These describe the specific actions or functionalities that the system must perform. Examples include user authentication, crop data input, weather data retrieval, soil moisture data processing, irrigation schedule generation, real-time recommendation provision, and user interface display.

ii. **Non-Functional Requirements:** These define the quality attributes of the system, such as performance, usability, reliability, security, scalability, maintainability, and portability.

Prioritization: Once categorized, the requirements will be prioritized based on several factors, including:

i. **Importance:** How critical is the requirement to the core functionality and the achievement of the project objectives?

ii. **Urgency:** How time-sensitive is the requirement from the stakeholders' perspective?

iii. **Feasibility:** How technically challenging and resource-intensive is it to implement the requirement?

iv. **Value:** What is the potential benefit or impact of implementing the requirement for the stakeholders?

A prioritization matrix or a similar technique (e.g., MoSCoW - Must have, Should have, Could have, Won't have) will be used to ensure that the development efforts are focused on delivering the most valuable and critical features first, aligning with the iterative nature of the Kanban methodology.

3.3.3.1 Functional Requirements

Based on the scope of the study, the key functional requirements of the smart crop irrigation scheduling system include:

i. **User Authentication and Authorization:** Securely manage user access to the system.

ii. **Crop Data Input:** Allow farmers to input details about their crops, such as type, growth stage, and location.

iii. **Historical Weather Data Retrieval:** Access and process historical weather data relevant to the farmers' locations.

iv. **Real-time Weather Data Retrieval:** Integrate with weather APIs to obtain current and forecasted weather information.

v. **Soil Moisture Data Processing:** Enable the input or integration of soil moisture data from sensors or manual measurements.

vi. **Irrigation Schedule Generation:** Utilize the CART algorithm to generate optimal irrigation schedules based on historical and real-time data, crop type, and soil moisture.

vii. **Real-time Irrigation Recommendation Provision:** Provide dynamic watering recommendations based on current environmental conditions and sensor data.

viii. **User Interface Display:** Present the generated irrigation schedules and real-time recommendations in a clear, intuitive, and actionable format through a user-friendly interface.

3.3.3.2 Non-Functional Requirements

The smart crop irrigation scheduling system will be designed to meet the following key non-functional requirements:

i. **Performance:** The system should generate irrigation schedules and provide real-time recommendations with minimal delay to ensure timely decision-making. Data processing should be efficient to handle large datasets.

ii. **Usability:** The user interface must be intuitive, easy to navigate, and require minimal technical expertise from the farmers. Information should be presented clearly and concisely.

iii. **Reliability:** The system should be dependable and consistently available, with minimal downtime. Data accuracy and fault tolerance are crucial for providing trustworthy irrigation advice.

iv. **Security:** User data and system information must be protected against unauthorized access and breaches, ensuring data privacy.

v. **Scalability:** The system should be designed to accommodate a growing number of users, crops, and data without significant performance degradation.

vi. **Maintainability:** The system's architecture and codebase should be structured in a way that allows for easy modification, updates, and bug fixes.

3.3.3.4 Requirements Validation

Within the Agile Kanban framework, requirements validation will be an ongoing and iterative process, ensuring that the developed system aligns with the stakeholders' needs and expectations. The following methods will be employed for requirements validation:

i. **Regular Feedback Loops:** Throughout the development process, functional increments and prototypes of the system will be regularly presented to farmers for their feedback. This continuous feedback loop will allow for early identification and correction of any discrepancies between the developed features and the actual requirements.

ii. **User Story Mapping and Review:** User stories, which represent specific user needs and functionalities, will be reviewed and validated by stakeholders to ensure they accurately reflect their requirements.

iii. **Prototype Demonstrations:** Working prototypes of the user interface and core functionalities will be demonstrated to farmers to gather direct feedback on usability, clarity, and effectiveness. This hands-on interaction will help validate the design and functionality of the system from the user's perspective.

iv. **Continuous Integration and Testing:** While primarily a development practice, the continuous integration and testing of the system will ensure that the implemented

v. features consistently meet the defined functional and non-functional requirements throughout the development lifecycle. Any deviations or issues identified during testing will be addressed promptly, contributing to the ongoing validation of the requirements.

This multi-faceted approach to requirements specification, encompassing thorough gathering, analysis, and continuous validation, will provide a robust foundation for the successful development of the smart crop irrigation scheduling system.

3.4. Summary

This chapter outlines the methodology for developing the smart crop irrigation scheduling system using the Agile Kanban framework, which emphasizes iterative development and continuous feedback. Stakeholder needs—primarily farmers, with input from researchers and investors—were identified through surveys and literature review. Requirements were categorized into functional and non-functional types, then prioritized. Validation involved feedback loops, user story reviews, prototype demos, and ongoing testing to ensure alignment with stakeholder expectations.

3.7 Gantt Chart and Budget

3.7.1 Gantt Chart

MONTH		March				April				May				June			
WEEK		**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
	Project Proposal																
	Literature Review																
	Requirement Gathering																
	Design Specification																
	System Development																
	Integration Testing																
	Document																
	Handover Of Product																

3.7.2 Budget

ITEM	COST
Internet	K2000
Printing and Stationary	K1500
Transportation	K500
Total	K4000

References

[1] S. Vijaya, D. V. Kirange, B. Satyannarayana, and A. Garg, "Developing AI-powered Systems to Optimize Planting , Irrigation , and Harvest Processes for Increased Agricultural Productivity," vol. 28, no. 1, pp. 2324–2330, 2024.

[2] M. Tabassum, "Precision Irrigation Scheduling using Real-Time Environmental Data," vol. 01, no. 3, pp. 20–34, 2024.

[3] Olabimpe Banke Akintuyi, "AI in agriculture: A comparative review of developments in the USA and Africa," *Open Access Res. J. Sci. Technol.*, vol. 10, no. 2, pp. 060–070, 2024, doi: 10.53022/oarjst.2024.10.2.0051.

[4] P. Christias, I. N. Daliakopoulos, T. Manios, and M. Mocanu, "Comparison of three computational approaches for tree crop irrigation decision support," *Mathematics*, vol. 8, no. 5, 2020, doi: 10.3390/MATH8050717.

[5] B. Askaraliev, K. Musabaeva, B. Koshmatov, K. Omurzakov, and Z. Dzhakshylykova, "Development of modern irrigation systems for improving efficiency, reducing water consumption and increasing yields," *Mach. Energ.*, vol. 15, no. 3, pp. 47–59, 2024, doi: 10.31548/machinery/3.2024.47.

[6] "A1 - 1 Sustainability, food security and climate change: three intertwined challenges | Climate Smart Agriculture Sourcebook | Food and Agriculture Organization of the United Nations." Accessed: Mar. 05, 2025. [Online]. Available: https://www.fao.org/climate-smart-agriculture-sourcebook/concept/module-a1-introducing-csa/chapter-a1-1/en/

[7] C. M. Viana, D. Freire, P. Abrantes, J. Rocha, and P. Pereira, "Agricultural land systems importance for supporting food security and sustainable development goals: A systematic review," *Sci. Total Environ.*, vol. 806, p. 150718, Feb. 2022, doi: 10.1016/J.SCITOTENV.2021.150718.

[8] G. Nikolaou, D. Neocleous, A. Christou, E. Kitta, and N. Katsoulas, "Implementing Sustainable Irrigation in Water-Scarce Regions under the Impact of Climate Change," *Agron. 2020, Vol. 10, Page 1120*, vol. 10, no. 8, p. 1120, Aug. 2020, doi: 10.3390/AGRONOMY10081120.

[9] T. Talaviya, D. Shah, N. Patel, H. Yagnik, and M. Shah, "Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides," *Artif. Intell. Agric.*, vol. 4, pp. 58–73, 2020, doi: 10.1016/j.aiia.2020.04.002.

[10] Phv. Professor, V. Parbhani Rama Shankar Singh, and D. Sinha, "Problem Soils And Their Management Practices i PROBLEM SOILS AND THEIR MANAGEMENT PRACTICES," no. December, 2009, [Online]. Available: www.parmarpublisher.com

[11] A. L. Srivastav, R. Dhyani, M. Ranjan, S. Madhav, and M. Sillanpää, "Climate-resilient strategies for sustainable management of water resources and agriculture," *Environ. Sci. Pollut. Res. 2021 2831*, vol. 28, no. 31, pp. 41576–41595, Jun. 2021, doi: 10.1007/S11356-021-14332-4.

[12] E. A. Abioye *et al.*, "A review on monitoring and advanced control strategies for precision irrigation," *Comput. Electron. Agric.*, vol. 173, p. 105441, Jun. 2020, doi: 10.1016/J.COMPAG.2020.105441.

[13] M. R. Barbosa Júnior *et al.*, "Precision agriculture in the United States: A comprehensive meta-review inspiring further research, innovation, and adoption," *Comput. Electron. Agric.*, vol. 221, p. 108993, Jun. 2024, doi: 10.1016/J.COMPAG.2024.108993.

[14] H. Wei *et al.*, "Irrigation with Artificial Intelligence: Problems, Premises, Promises," *Human-Centric Intell. Syst.*, vol. 4, no. 2, pp. 187–205, 2024, doi: 10.1007/s44230-024-00072-4.

[15] Z. Sun, G. Wang, P. Li, H. Wang, M. Zhang, and X. Liang, “An improved random forest based on the classification accuracy and correlation measurement of decision trees,” *Expert Syst. Appl.*, vol. 237, p. 121549, 2023, doi: 10.1016/j.eswa.2023.121549.

[16] A. Elshaikh, E. Elsheikh, and J. Mabrouki, “Applications of Artificial Intelligence in Precision Irrigation,” *J. Environ. Earth Sci.*, vol. 6, no. 2, pp. 176–186, 2024, doi: 10.30564/jees.v6i2.6679.

[17] C. Ingrao, R. Strippoli, G. Lagioia, and D. Huisingh, “Water scarcity in agriculture: An overview of causes, impacts and approaches for reducing the risks,” *Heliyon*, vol. 9, no. 8, p. e18507, 2023, doi: https://doi.org/10.1016/j.heliyon.2023.e18507.

[18] M. Muhammad *et al.*, “Soil salinity and drought tolerance: An evaluation of plant growth, productivity, microbial diversity, and amelioration strategies,” *Plant Stress*, vol. 11, p. 100319, 2024, doi: https://doi.org/10.1016/j.stress.2023.100319.

[19] J. Kairo, “Machine Learning Algorithms for Predictive Maintenance in Manufacturing,” *J. Technol. Syst.*, vol. 6, pp. 66–79, 2024, doi: 10.47941/jts.2144.

[20] G. Areo, “Sustainability in Manufacturing: Leveraging AI and Data Analytics to Minimize Waste and Carbon Footprint,” 2025.

[21] E. Frank and E. Ok, “The Influence of Artificial Intelligence on Education: Enhancing Personalized Learning Experiences,” 2024.

[22] Z. Xu, “AI in education: Enhancing learning experiences and student outcomes,” *Appl. Comput. Eng.*, vol. 51, pp. 104–111, 2024, doi: 10.54254/2755-2721/51/20241187.

[23] D. Tamayo-Vera, X. (Xander) Wang, and M. Mesbah, “A Review of Machine Learning Techniques in Agroclimatic Studies,” *Agriculture*, vol. 14, p. 481, 2024, doi: 10.3390/agriculture14030481.

[24] E. Wen, H. Kang, and D. Vistro, “The Application of Machine Learning in Agriculture Sustainability: A Review,” *Int. J. Data Sci. Adv. Anal.*, vol. 4, pp. 66–70, 2022, doi: 10.69511/ijdsaa.v4i4.94.

[25] C. Chakraborty, M. Bhattacharya, S. Pal, and S.-S. Lee, “From machine learning to deep learning: Advances of the recent data-driven paradigm shift in medicine and healthcare,” *Curr. Res. Biotechnol.*, vol. 7, p. 100164, 2024, doi: https://doi.org/10.1016/j.crbiot.2023.100164.

[26] M. Javaid, A. Haleem, R. Pratap Singh, R. Suman, and S. Rab, “Significance of machine learning in healthcare: Features, pillars and applications,” *Int. J. Intell. Networks*, vol. 3, pp. 58–73, 2022, doi: https://doi.org/10.1016/j.ijin.2022.05.002.

[27] S. Violino *et al.*, “A data-driven bibliometric review on precision irrigation,” *Smart Agric. Technol.*, vol. 5, p. 100320, 2023, doi: https://doi.org/10.1016/j.atech.2023.100320.

[28] I. Lakhiar *et al.*, “A Review of Precision Irrigation Water-Saving Technology under Changing Climate for Enhancing Water Use Efficiency, Crop Yield, and Environmental Footprints,” *Agriculture*, vol. 14, p. 1141, 2024, doi: 10.3390/agriculture14071141.

[29] D. Balas, D. Thakor, and S. Dhakad, “Irrigation Methods,” 2024, pp. 232–254.

[30] N. Abu *et al.*, “Internet of Things Applications in Precision Agriculture: A Review,” *J. Robot. Control*, vol. 3, pp. 338–347, 2022, doi: 10.18196/jrc.v3i3.14159.

[31] W. Li *et al.*, “Review of Sensor Network-Based Irrigation Systems Using IoT and Remote Sensing,” *Adv. Meteorol.*, vol. 2020, p. 14, 2020, doi: 10.1155/2020/8396164.

[32] M. Waqas, A. Naseem, U. W. Humphries, P. T. Hlaing, P. Dechpichai, and A. Wangwongchai, “Applications of machine learning and deep learning in agriculture: A comprehensive review,”

Green Technol. Sustain., vol. 3, no. 3, p. 100199, 2025, doi: https://doi.org/10.1016/j.grets.2025.100199.

[33] J. Botero-Valencia *et al.*, "Machine Learning in Sustainable Agriculture: Systematic Review and Research Perspectives," *Agriculture*, vol. 15, p. 377, 2025, doi: 10.3390/agriculture15040377.

[34] L. Preite and G. Vignali, "Artificial intelligence to optimize water consumption in agriculture: A predictive algorithm-based irrigation management system," *Comput. Electron. Agric.*, vol. 223, p. 109126, 2024, doi: 10.1016/j.compag.2024.109126.

[35] A. Pagano *et al.*, "Machine learning models to predict daily actual evapotranspiration of citrus orchards under regulated deficit irrigation," *Ecol. Inform.*, vol. 76, p. 102133, 2023, doi: https://doi.org/10.1016/j.ecoinf.2023.102133.

[36] A. Jamal *et al.*, "Real-Time Irrigation Scheduling Based on Weather Forecasts, Field Observations, and Human-Machine Interactions," *Water Resour. Res.*, vol. 59, 2024, doi: 10.1029/2023WR035810.

[37] S. Thakur, "CLIMATE CHANGE IMPACTS ON IRRIGATION SYSTEM AND ITS ADAPTATION NEED," vol. 10, pp. 29–38, 2018.

[38] P. Hanzlik, F. Kozisek, and J. Pavlicek, "Design of intelligent decision support systems in agriculture," *Int. J. Math. Comput. Simul.*, vol. 9, pp. 113–118, 2015.

[39] FAO, *Water for Sustainable Food and Agriculture Water for Sustainable Food and Agriculture*. 2017. [Online]. Available: https://bit.ly/3GJtCtP

[40] D. K. Asmamaw *et al.*, "Soil and irrigation water management: Farmer's practice, insight, and major constraints in upper blue Nile basin, Ethiopia," *Agric.*, vol. 11, no. 5, 2021, doi: 10.3390/agriculture11050383.

[41] U. Nations, *The state of the world's land and water resources for food and agriculture: Managing systems at risk*, vol. 9780203142. 2013. doi: 10.4324/9780203142837.

[42] R. Arabelli, A. Pooja, S. S. Nanditha, K. Deepa, M. Ajaybabu, and S. M. Ahmed, "Exploring Water Quality Prediction Using Machine Learning---An Efficient and Emerging Method of Evaluation," in *Proceedings of the Third International Conference on Cognitive and Intelligent Computing, Volume 1*, A. Kumar, G. Ghinea, and S. Merugu, Eds., Singapore: Springer Nature Singapore, 2025, pp. 379–391.

[43] M. K. Senapaty, A. Ray, and N. Padhy, "A Decision Support System for Crop Recommendation Using Machine Learning Classification Algorithms," *Agric.*, vol. 14, no. 8, 2024, doi: 10.3390/agriculture14081256.

[44] D. Mienye and N. Jere, "A Survey of Decision Trees: Concepts, Algorithms, and Applications," *IEEE Access*, vol. PP, p. 1, 2024, doi: 10.1109/ACCESS.2024.3416838.

[45] N. Tantalaki, S. Souravlas, and M. Roumeliotis, "Data-Driven Decision Making in Precision Agriculture: The Rise of Big Data in Agricultural Systems," *J. Agric. Food Inf.*, vol. 20, pp. 344–380, 2019, doi: 10.1080/10496505.2019.1638264.

[46] S. O. Araújo, R. S. Peres, J. C. Ramalho, F. Lidon, and J. Barata, "Machine Learning Applications in Agriculture: Current Trends, Challenges, and Future Perspectives," *Agronomy*, vol. 13, no. 12, 2023, doi: 10.3390/agronomy13122976.

[47] Z. Shu *et al.*, "Evaluation of the Impact of Multi-Source Uncertainties on Meteorological and Hydrological Ensemble Forecasting," *Engineering*, vol. 24, pp. 212–228, 2023, doi: https://doi.org/10.1016/j.eng.2022.06.007.

[48] R. Sui and E. Vories, "Comparison of Sensor-Based and Weather-Based Irrigation

Scheduling,” *Appl. Eng. Agric.*, vol. 36, pp. 375–386, 2020, doi: 10.13031/aea.13678.

[49] D. B. Olawade, O. Z. Wada, A. O. Ige, B. I. Egbewole, A. Olojo, and B. I. Oladapo, “Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions,” *Hyg. Environ. Heal. Adv.*, vol. 12, p. 100114, 2024, doi: https://doi.org/10.1016/j.heha.2024.100114.

[50] D. M. Dave and B. Mittapally, “Data Integration and Interoperability in IOT: Challenges, Strategies and Future Direction,” *Int. J. Comput. Eng. Technol.*, vol. 15, pp. 45–60, 2024.

[51] B. Et-taibi *et al.*, “Enhancing water management in smart agriculture: A cloud and IoT-Based smart irrigation system,” *Results Eng.*, vol. 22, p. 102283, 2024, doi: https://doi.org/10.1016/j.rineng.2024.102283.

[52] S. Pandeya, B. R. Gyawali, and S. Upadhaya, “Factors Influencing Precision Agriculture Technology Adoption Among Small-Scale Farmers in Kentucky and Their Implications for Policy and Practice,” *Agriculture*, vol. 15, no. 2, 2025, doi: 10.3390/agriculture15020177.

[53] H. J. Smidt and O. Jokonya, “Factors affecting digital technology adoption by small-scale farmers in agriculture value chains (AVCs) in South Africa,” *Inf. Technol. Dev.*, vol. 28, no. 3, pp. 558–584, 2022, doi: 10.1080/02681102.2021.1975256.

[54] A. Patokar and V. Gohokar, “design and development of intuitive android application for smart farming,” *Curr. Agric. Res. J.*, vol. 12, 2024, doi: 10.12944/CARJ.12.1.33.

[55] Y. Kang, S. Khan, and X. Ma, “Climate change impacts on crop yield, crop water productivity and food security – A review,” *Prog. Nat. Sci.*, vol. 19, no. 12, pp. 1665–1674, 2009, doi: https://doi.org/10.1016/j.pnsc.2009.08.001.

[56] H. H. Sarma, S. Borah, N. Dutta, N. Sultana, H. Nath, and B. Das, “Innovative Approaches for Climate Resilient Farming: Strategies against Environmental Shifts and Climate Change,” *Int. J. Environ. Clim. Chang.*, vol. 14, pp. 217–241, 2024, doi: 10.9734/ijecc/2024/v14i94407.

[57] L. Umutoni and V. Samadi, “Application of machine learning approaches in supporting irrigation decision making: A review,” *Agric. Water Manag.*, vol. 294, p. 108710, 2024, doi: https://doi.org/10.1016/j.agwat.2024.108710.