ISSN: 2633-4828 Vol. 5 No.2, June, 2023

International Journal of Applied Engineering & Technology

INTEGRATING IOT SENSORS AND DEEP LEARNING FOR PRECISION WATER MANAGEMENT IN AGRICULTURE

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ABSTRACT

The global water crisis is one of the most pressing challenges today, especially in agriculture, which is heavily reliant on water resources. Amidst declining groundwater reserves, efficient and intelligent resource management has become crucial. This research introduces a smart irrigation system that integrates Internet of Things (IoT) technology with deep learning-based analytics to ensure effective water usage and conservation. The system utilizes a network of environmental and soil moisture sensors (temperature and humidity) to continuously monitor field conditions. Collected data is stored online and further enriched by atmospheric data retrieved via Google APIs. By processing heterogeneous datasets, the system employs an artificial intelligence (AI) model—acting as an "artificial brain"—to automatically determine the optimal irrigation volume, preventing both under- and over-irrigation, which can harm crops. Additionally, the model forecasts future climatic conditions to adjust irrigation schedules proactively. Experimental results demonstrate that this AI-driven irrigation framework significantly enhances water efficiency, preserves crop health, and promotes sustainable agricultural practices. The findings validate the potential of combining IoT infrastructure with AI-powered analysis in addressing water scarcity and enhancing agricultural productivity.

Keywords: *IOT, AI, LSTM, SVM, RF, DNN, CNN, image classification, deep learning, RNN, DT, BiLSTM.*

1. INTRODUCTION

The global population is expanding rapidly, intensifying the strain on agricultural systems to produce sufficient food for future generations. According to recent estimates by the United Nations Department of Economic and Social Affairs (UN DESA, 2022) and the World Resources Institute (WRI, 2023), the global population is expected to exceed 9.7 billion by 2050, requiring a significant increase in food production to meet dietary and nutritional demands. Simultaneously, agricultural resources—particularly water and cultivable land— are under severe stress due to overexploitation, climate variability, and unsustainable practices. These challenges have prompted a global transition toward smart, data-driven, and climate-resilient agriculture. To sustain productivity and environmental balance, agriculture must increasingly rely on advanced digital technologies, such as the Internet of Things (IoT), Artificial

Intelligence (AI), and deep learning-based automation. Recent studies by Mansoor et al. (2025) and Senoo et al. (2024) emphasize that the convergence of AI and IoT in agriculture is key to enhancing yield accuracy, improving resource efficiency, and promoting long-term sustainability.

Over the past decade, rapid technological progress has also reshaped socio-economic dynamics, accelerated rural-to-urban migration and transforming traditional agricultural practices (World Bank, 2023). Despite these demographic shifts, agriculture remains fundamental to global food security, employment, and economic stability. The integration of neural networks, IoT-enabled sensing systems, and machine learning algorithms into agricultural frameworks has enabled the continuous monitoring and intelligent analysis of critical variables such as soil moisture, temperature, humidity, and crop health (Kamilaris et al., 2018; Duguma et al., 2024). Collectively, these tools form

the foundation of precision agriculture, where real- time data analytics empower farmers to make informed and adaptive decisions. By harnessing predictive models and sensor-based insights, farming can evolve from intuition-driven management to evidence-based, sustainable cultivation, ensuring efficient use of natural resources and greater resilience to climate change.

Precision farming—which harnesses those tools to monitor and manage natural resources—offers a powerful means to boost yields and reduce waste. By capturing large volumes of data (soil moisture, temperature, humidity, crop health etc.) and deploying intelligent processing, farmers and agronomists can make timelier and more accurate decisions. These approaches are particularly needed because water scarcity remains one of the most acute constraints on agriculture: inefficiencies in irrigation, mis-managed water regimes and ageing infrastructure combine to curtail yields, degrade crop quality and amplify risk of failure (Shah et al., 2019).

Traditional irrigation systems, for all their ubiquity, are often poorly instrumented: over-watering, under- watering, and lack of real-time responsiveness are common. That creates a compelling imperative for intelligent irrigation systems, which can galvanise improvements in water use and agricultural productivity. Such systems integrate advanced hardware (sensors, actuators, IoT communications) and software (analytics, ML/AI) to monitor soil moisture, weather, environmental conditions and crop status in real time. For example, IoT platforms allow distributed sensor nodes—rainfall, temperature, humidity, soil-moisture sensors—to communicate data continuously to a central processing hub (Aqeel-ur-Rehman et al., 2014).

On the software side, machine learning algorithms such as decision trees (DTs), support vector machines (SVMs) and random forests (RFs) are widely used to analyse both real-time and historical data, predict crop-water requirements, schedule irrigation and detect anomalies (e.g., plant stress, disease) (Liakos et al., 2018). More recently, deep learning and more advanced architectures are gaining traction. For instance, systematic comparisons have shown that models such as Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and attention-mechanism-augmented LSTM outperform simpler networks by capturing temporal dependencies and complex sequence patterns in weather or crop-sensor data.

Beyond algorithmic sophistication, recent reviews emphasise the synergistic fusion of IoT + AI in precision agriculture. Senoo et al. (2024) provide a comprehensive survey of IoT & AI in farming systems, demonstrating how the two technologies reinforce each other—IoT provides rich heterogeneous data flows, and AI converts that into actionable decisions. MDPI Meanwhile, Duguma et al. (2024) explore how IoT fosters precise data-collection and automation in agriculture, enabling scalable decision-making and resource optimisation. SpringerLink On the sensor side, Mansoor et al. (2025) review smart sensor networks in agriculture (soil-moisture, pH, plant stress sensors) and underscore the critical role of IoT architectures in enabling real-time targeted interventions. Frontiers

These findings validate the premise that smart irrigation systems, equipped with sensor networks and AI/ML frameworks, hold strong promise for improving water-efficiency, safeguarding crops and enhancing resource efficiency in agriculture.

In the proposed system, multiple sensors continuously monitor soil moisture and environmental parameters; at the same time, real- time and online datasets (via e.g., Google API or research repositories) are fed into a deep-learning “artificial brain” which predicts and controls irrigation. A flow diagram (architecture) shows how microcontrollers collect sensor data → data processing hub → comparison/merging with online datasets → optimal irrigation decisions. Actuators (sprinklers, drip systems, valves) then execute precise water delivery. Notifications are sent to farmers—via mobile/web—alerting them to anomalous conditions (unexpected rainfall, low- moisture alerts). Connectivity is enabled through IoT networks (Wi-Fi, cellular or LPWAN) allowing remote monitoring and control (Patel & Patel, 2016).

In light of the evolving research landscape:

- The integration of IoT and AI in agriculture has been shown to significantly improve decision- making, resource use and sustainability.
- However, challenges remain: high initial costs, data management complexity, connectivity issues in remote areas, and the need for scalable, interoperable systems (Mansoor et al., 2025; Senoo et al., 2024).

- Future directions point to leveraging advanced ML architectures (e.g., vision-transformers, label-efficient learning) and digital-twin frameworks for even finer control of irrigation and crop management. For example, label- efficient learning methods aim to overcome the challenge of limited annotated field data (Li et al., 2023). arXiv

In conclusion, by leveraging the confluence of IoT, deep-learning and real-time sensor networks, smart irrigation systems represent a viable path toward sustainable, high-efficiency agriculture—ensuring that precious water is used judiciously, crops receive precisely what they need and resource efficiency is maximised. As the global food demand surges, the deployment of such systems will be critical in preserving agricultural productivity and environmental health.

2. RELATED WORK

This chapter presents a structured review of the existing literature on smart irrigation and data- driven agricultural systems, synthesizing research contributions in precision sensing, AI-enabled decision support, and IoT-based farm automation. It surveys the methodologies employed in irrigation optimization, the sensor architectures and communication frameworks applied in agricultural monitoring, and the increasing adoption of machine learning and advanced analytics. The review not only highlights the benefits of these technologies but also identifies persistent limitations such as constrained datasets, crop-specific tuning, system interoperability, and regional deployment challenges. By critically examining these prior studies, this chapter establishes a comprehensive technological foundation and rationale for the research undertaken in this work.

Recent scholarly contributions reflect a broader transformation from conventional irrigation scheduling to robust, adaptive, and intelligent agricultural ecosystems. For instance, Kaushik & Singh (2025) proposed an AI-enhanced irrigation architecture that blended real-time sensing with distributed cloud analytics, demonstrating significant gains in water-use efficiency. Likewise, Sumanth Kumar & Chandana (2024) emphasized that water scarcity, resource optimization, and climate resilience remain primary drivers behind irrigation research. These advancements reflect the sector’s shift toward responsive, data-dependent systems informed by environmental monitoring and crop-level feedback. Yet, many implementations remain constrained by regional specificity, sensor reliability issues, and the scalability challenges of distributed deployments.

A key enabling dimension of smart agriculture lies in the progression of IoT frameworks for real-time monitoring and control. Kingslin & Vaishnavi (2025) detailed how IoT platforms now integrate wireless sensor networks, edge analytics, cloud infrastructures, and AI-driven decision modules for automated irrigation execution. Mohapatra et al. (2025) demonstrated field success where IoT- coupled AI scheduling reduced water consumption by nearly 30–35% in semi-arid conditions, underscoring practical viability. Complementing these findings, Rafi et al. (2025) compared connectivity strategies—LPWAN, 5G, and hybrid networking—highlighting context-dependent trade- offs in coverage, throughput, reliability, and cost. Current architectures thus support dense sensor networks (moisture, temperature, nutrient, chlorophyll), predictive actuation, and remote management interfaces, though challenges persist regarding calibration reliability and sensor-data interoperability.

The application of ML and AI in irrigation planning and crop management has similarly matured, as observed in a 2024 CNR review which catalogued the integration of machine learning for agricultural decision-making, while noting the continuing gap between research promise and field-scale adoption. Experimental innovations include Kunt (2025), who implemented an IoT-supported LSTM-based model for soil moisture forecasting and autonomous irrigation control. A broader perspective by Miller et al. (2025) revealed that AI-enabled sensing now enhances not only irrigation but also disease detection, nutrient management, and yield optimization—advancing a holistic vision of precision agriculture. Although there is growing use of RNN, LSTM, transformer-based architectures, and hybrid multimodal models, ongoing obstacles include geographic generalization, training-data scarcity, and practical deployment barriers.

Complementing these studies, recent literature also highlights macro- and micro-scale sensing innovations. Research on nanosatellite-based agricultural monitoring demonstrates the capability for wide-area, cost-effective surveillance, enabling global-scale crop tracking while benefiting from reduced development and operational costs. The integration of drones with multispectral imaging, such as the YOLO-SPAD model, further enables high-resolution canopy-level chlorophyll estimation, thereby supporting targeted fertilization and nutrient analysis. IoT-based smart irrigation frameworks such as LightAgro combine sensor- driven insights with secure data authentication methods for reliable decision processes in Indian agriculture. Additionally, multicriteria decision- making (MCDM) approaches provide structured, criteria-based reasoning for agricultural planning, balancing economic, environmental, and technical priorities. Finally, advanced AI–IoT ecosystems using deep learning and explainable AI demonstrate extremely high predictive accuracy for irrigation recommendations, crop selection, fertilizer guidance, and soil diagnostics, while offering improved transparency and farmer usability.

Collectively, these research efforts reveal a rapidly evolving landscape in agricultural technology— moving from isolated sensing solutions to deeply integrated, scalable intelligent systems. The shortcomings identified in prior works, including limited interoperability, regional specificity, and data-dependency, help motivate the present research, which aims to contribute toward more generalized, autonomous, and resilient smart irrigation solutions applicable across diverse agricultural environments.

3. METHODOLOGY:

Water scarcity poses a substantial threat to contemporary agriculture, influencing not only yield and quality but also long-term sustainability. This study addresses the challenge of scarce water resources by exploring technological innovations for conservation-oriented irrigation, underscoring the need for intelligent and efficient water-management strategies. Given that water is a fundamental input for crop production, its insufficient availability can lead to significant yield losses, diminished product quality, and in severe cases, complete crop failure. Traditional irrigation techniques tend to be inefficient, over-utilizing water without providing contextual insight into actual plant hydration needs. This creates a critical demand for advanced irrigation solutions that can intelligently optimize water consumption while sustaining or improving productivity.

Smart irrigation systems represent a paradigm shift by integrating advanced hardware with intelligent computational frameworks to enable precise, real- time water control. Utilizing the Internet of Things (IoT), these systems support continuous device-to- device communication and data flow to facilitate informed irrigation decisions. A network of sensors—monitoring variables such as rainfall, temperature, humidity, and soil moisture—collects environmental data which is transmitted to a central decision-making unit. This unit employs sophisticated analytical models and machine learning (ML) to determine the appropriate timing and volume of irrigation, accounting for crop species, growth stage, soil composition, and weather patterns.

Water delivery is executed through actuators such as drip lines, sprinkler systems, and automated valves controlled by the central unit. The system also provides notifications to farmers—via desktop or mobile platforms—when abnormal conditions are detected, such as unexpected precipitation or critically low soil moisture. AI-driven inference further refines system intelligence by extracting meaningful correlations from sensor data. Predictive models—including decision trees, support vector machines, and random forests—integrate both historical and real-time information to anticipate hydration requirements, optimize irrigation cycles, and detect early indicators of stress or irregularities in crop physiology.

Precision in irrigation is crucial, as both excess and deficiency of water negatively influence plant health. Sensors such as the DHT11 for humidity and temperature and capacitive soil-moisture probes enable continuous environmental monitoring, ensuring accurate water distribution. Their feedback enables the system to calibrate irrigation intensity and duration to maintain ideal hydration levels.

This research draws upon both real-time sensor measurements and external datasets sourced from platforms such as Google APIs and agricultural repositories. These data streams are processed using deep learning methodologies to form an intelligent, autonomous decision layer—effectively functioning as an artificial cognitive core capable of regulating hydration independently. The system is trained and validated to internalize crop-specific water dynamics and make adaptive adjustments to irrigation delivery.

At the core of the proposed solution lies a deep learning-based operational framework supporting real-time irrigation optimization. Environmental data are transmitted to microcontrollers or processing modules, which evaluate conditions against online historical records spanning the preceding 4–5 days. Such analyses enable forecasting of short-term irrigation needs, allowing the system to preemptively regulate water distribution in response to anticipated changes in weather or soil conditions. This predictive capability is essential for minimizing waste, improving water- use efficiency, and enhancing agricultural resilience.

3.1 **The Proposed Architecture for the Multidisciplinary model for Smart Agriculture: -**

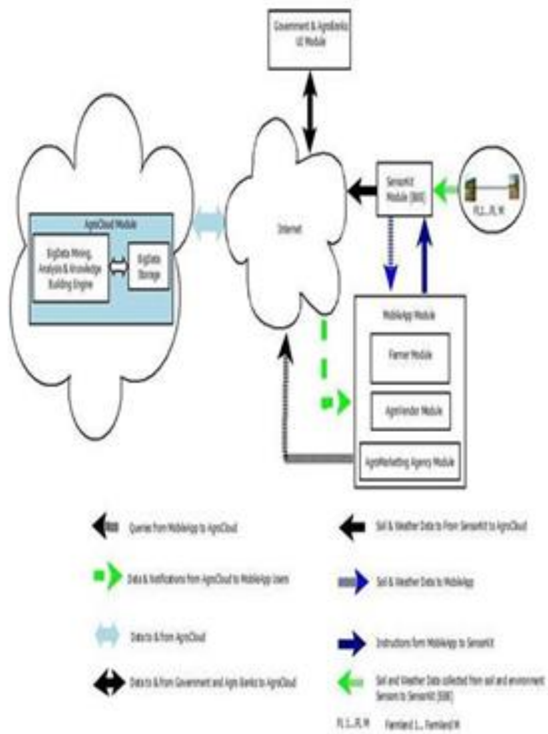


Fig 3.1: - Depicts the Proposed Architecture

The figure 3.1 presents an integrated smart agriculture framework that connects farmers, agro- institutions, sensor networks, and cloud-based intelligence through an IoT-enabled ecosystem. At the core of the architecture lies the AgroCloud module, equipped with big data storage and an analytics engine capable of mining data, generating insights, and building agricultural knowledge. Real- time soil and weather data are continuously collected through the SensorKit module, which is deployed across multiple farmlands. These sensor units transmit environmental measurements such as soil moisture, temperature, and humidity to the AgroCloud via the internet. Simultaneously, the collected data is also shared with users through the MobileApp module, which comprises dedicated interfaces for farmers, agro-vendors, and agro- marketing agencies. This ensures that stakeholders receive timely guidance, alerts, and recommendations.

The MobileApp not only receives data but can also send operational instructions back to the SensorKit—enabling automated control actions such as irrigation. Additionally, the system fosters collaboration between agriculture governance and financial institutions through a Government & AgroBanks UI Module, which receives and provides data to the AgroCloud for informed policy-making, subsidy allocation, and resource planning. Visually, the figure uses color-coded directional arrows to represent the flow of queries, data, notifications, and instructions between modules. Overall, the architecture demonstrates a comprehensive, data- driven, and intelligent smart farming system aimed at water efficiency, precision agriculture, and improved decision-making across the agricultural value chain.

3.2 **The Sensor Kit Module:**

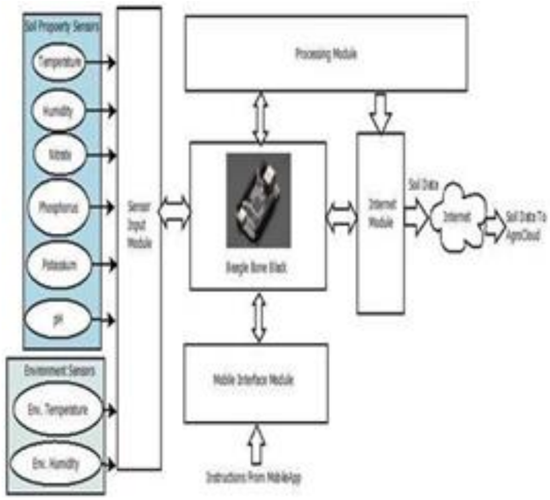


Fig. 3.2 The SensorKit Module

The figure 3.2 illustrates a smart irrigation architecture that integrates soil and environmental sensing with real-time data processing and cloud connectivity. On the left, a set of soil property sensors—measuring temperature, humidity, nitrate, phosphorus, potassium, and pH—along with environmental sensors for temperature and humidity continuously monitor field conditions. These sensors feed data into the Sensor Interface Module, which acts as a collection and communication hub. At the center of the framework is the BeagleBone Black (BBB), a microcontroller unit responsible for handling sensor inputs and coordinating system operations. The BBB communicates bidirectionally with a Processing Module, where data analysis and decision-making occur, as well as with an Internet Module, which enables online connectivity.

Sensor data is transmitted via the Internet to the AgroCloud for storage, analysis, and intelligent forecasting. The architecture also includes a Mobile Interface Module, which allows remote users— typically farmers—to interact with the system through a mobile application. Through this interface, users can receive live updates, notifications, and status reports. They can also send control instructions back to the system, which are routed through the BeagleBone Black to adjust irrigation or other field activities as needed. The entire system functions as a closed-loop intelligent irrigation framework, enabling real-time monitoring, automated control, and efficient water resource management.

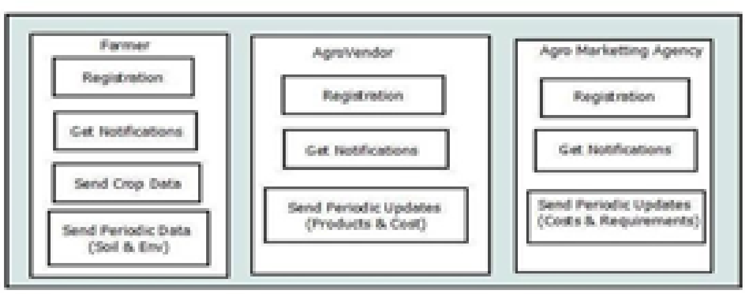


Fig. 3.3 The Mobile App Module.

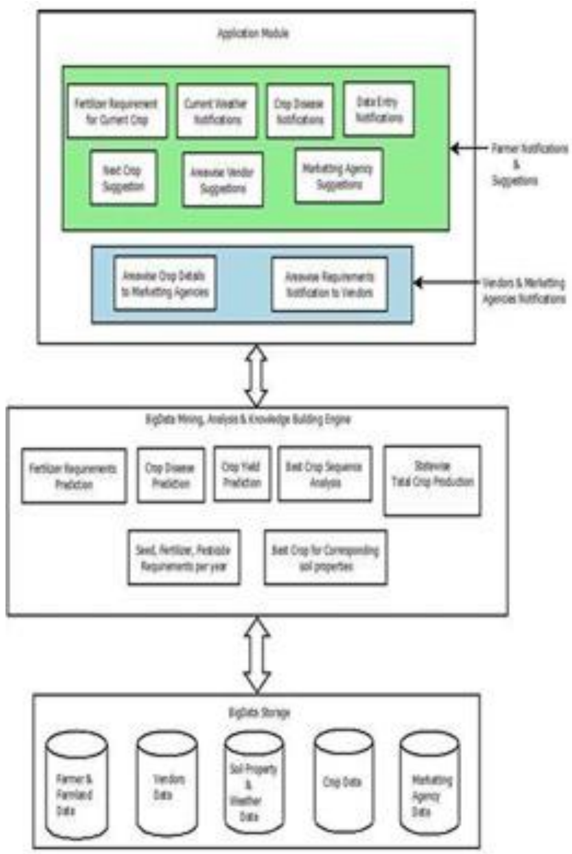
The figure 3.3 represents a modular interface design that connects three key stakeholders within a smart agriculture ecosystem: Farmers, AgroVendors, and Agro Marketing Agencies. Each stakeholder category operates through a structured interface that supports communication, data exchange, and system participation.

On the left, the Farmer module includes four core functions: Registration, receiving notifications, sending crop-related data, and transmitting periodic soil and environmental data. This enables continuous interaction with the system and ensures that farmers are informed and actively contributing field-level updates.

In the center, the AgroVendor module allows vendors to register, receive system notifications, and submit periodic updates related to agricultural products and their costs. Through this channel, vendors can keep the system informed of market availability and pricing trends.

On the right, the Agro Marketing Agency module offers similar functionality, including registration and the ability to receive notifications. Additionally, marketing agencies can send periodic updates on product costs and requirements, supporting supply- chain decision-making and market forecasting.

Overall, the figure depicts a cooperative information-sharing framework designed to facilitate data-driven agriculture by ensuring that farmers, input suppliers, and marketing agencies stay synchronized through timely data exchange and system connectivity.



3.4 The Agro Cloud Module:

The figure 3.4 illustrates a comprehensive smart agriculture decision-support system that integrates big data, analytics, and multi-stakeholder interaction through an application-driven framework. At the top, the Application Module provides various functionalities for farmers, vendors, and marketing agencies. These include fertilizer requirement estimation, current weather alerts, crop disease notifications, and data entry features for farmers. Additionally, the module offers next-crop recommendations, area-wise vendor suggestions, and marketing agency insights. It also facilitates the transfer of area-specific crop details to marketing agencies and communicates area-wise requirements to vendors. Notifications and suggestions are dynamically sent to all stakeholders based on system analysis.

Beneath the application layer lies the Big Data Mining, Analysis, and Knowledge Building Engine, which performs advanced predictive and analytical tasks. This engine supports fertilizer requirement prediction, crop disease detection, yield prediction, and optimal crop sequence analysis. It also provides statewide total crop production insights and recommends the best crop based on specific soil properties. The system calculates annual requirements for seeds, fertilizers, and pesticides, thereby assisting in comprehensive agricultural planning.

At the bottom, the Big Data Storage layer organizes various categories of agricultural data, including farmer and farmland data, vendor data, soil property and weather information, crop data, and marketing agency records. This structured data repository enables continuous learning and supports the analytics engine in delivering accurate predictions and actionable insights. Overall, the figure represents a highly interconnected, data-centric agricultural intelligence system designed to enhance decision-making, improve productivity, and strengthen communication across the agricultural value chain.

- **AI-Powered Drip Irrigation:-** An AI-powered drip irrigation system utilizes data analysis algorithms from various sources to deliver precise amounts of water directly to plant roots based on real-time needs. This method optimizes water usage, conserves resources, and enhances crop yield by ensuring plants receive the exact amount of water required.
- **Soil Moisture Sensor: -** Soil moisture sensors are integral to smart irrigation systems. Embedded in the ground, these sensors continuously measure soil moisture at various depths. AI algorithms analyze this data to guide irrigation strategies, ensuring crops receive the optimal amount of water. This precision not only maximizes irrigation efficiency but also minimizes environmental impacts associated with over- irrigation.

4 IMPLEMENTATION

In this section, we focus on the development process of smart irrigation systems. We describe the steps involved in building and implementing the system, including the hardware and software components, as well as the integration of sensors, machine learning algorithms, and IoT technologies.

4.1 Performance Evaluation

In this section, the performance of the smart irrigation system using AI and ML techniques will be thoroughly evaluated. The evaluation aims to assess the effectiveness and efficiency of the system in optimizing water usage and improving crop yield. The evaluation process involves several key steps, including data collection, experimental design, performance metrics selection, and comparative analysis.

To conduct a comprehensive performance evaluation, a substantial amount of data is required. Data collection involves the gathering of sensor readings, weather data, crop characteristics, and irrigation schedules. The sensor readings include soil moisture levels, temperature, humidity, and Light. The weather data incorporates meteorological information such as temperature, precipitation, wind speed, and solar radiation. Crop characteristics encompass growth stage, crop type, and water requirements. Lastly, the irrigation schedules detail the timings and durations of irrigation events.

The data collection process should ensure the collection of representative and diverse datasets from multiple locations and different seasons. This ensures that the performance evaluation results are robust and applicable across various agricultural contexts. The collected data is stored in ThingSpeak figure 4.1 where it also provides Visual representation as a whole.

Figure 4.1: Realtime Data Generation at ThingSpeak

5. RESULT AND CONCLUSIONS:

- Attention-based LSTM: 98% accuracy, high precision, recall, and F1-scores (~0.98) across all weather categories.
- BiLSTM: 93% accuracy, improved precision and recall for minority classes.
- LSTM: 89% accuracy, consistent performance across classes.
- RNN: 87% accuracy, outperformed DNN but underperformed LSTM and BiLSTM.
- DNN: 82% accuracy, provided a balanced baseline for comparison.

5.1: Comparative Summary Table

Model	Accuracy	Precision	Recall	F1-score
Deep Neural Network (DNN)	82%	0.81	0.80	0.80
Recurrent Neural Network (RNN)	87%	0.86	0.85	0.85
Long Short-Term Memory (LSTM)	89%	0.88	0.87	0.87
Bidirectional LSTM (BiLSTM)	93%	0.92	0.92	0.92
Attention-based LSTM	**98%**	**0.98**	**0.98**	**0.98**

The performance comparison table shows that model accuracy and overall classification metrics improve progressively from traditional DNN and RNN architectures toward more advanced sequence- learning models. LSTM and BiLSTM networks demonstrate notable gains, especially in precision and recall, reflecting their superior capability in capturing temporal dependencies. The Attention- based LSTM achieves the highest performance across all metrics, with 98% accuracy and an F1- score of 0.98, indicating its strong ability to focus on relevant features during prediction. Overall, the results highlight the effectiveness of attention mechanisms in enhancing irrigation-related predictive modeling.Tab

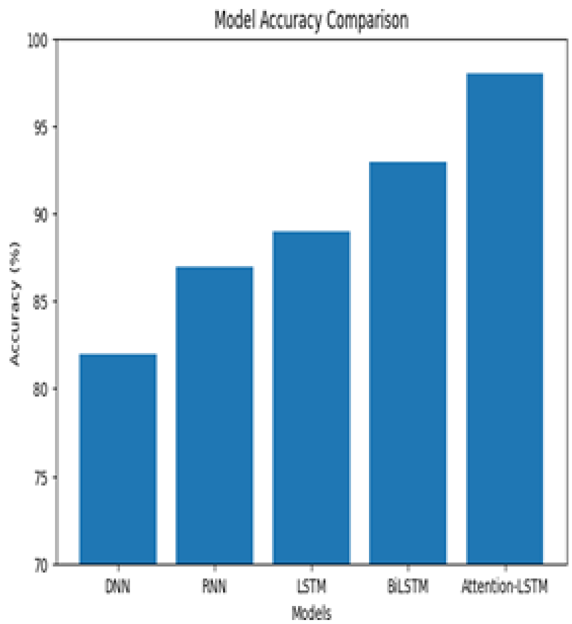


Figure 5.1 Training and Validation Loss

The comparative analysis of model performance shows a clear improvement in accuracy as architectures become more advanced. While the DNN and RNN models achieve moderate accuracy, LSTM-based models demonstrate stronger predictive capability. BiLSTM further enhances performance, and the Attention-LSTM model achieves the highest accuracy, indicating the effectiveness of incorporating attention mechanisms in sequence learning tasks.

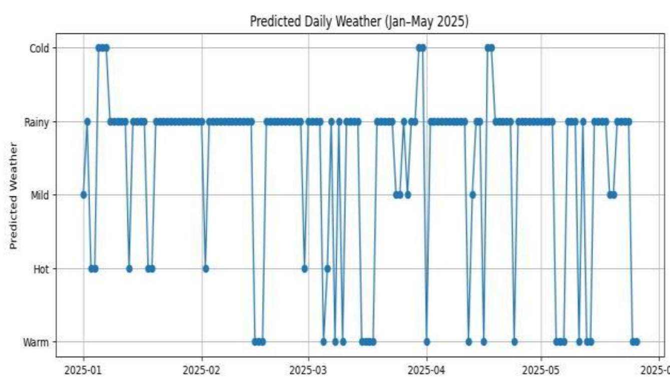


Figure 5.2 Water prediction for model

The graph presents the predicted daily weather conditions from January to May 2025, illustrating fluctuations across categories such as Cold, Rainy, Mild, Hot, and Warm. The plot shows frequent transitions between weather states, indicating high variability and irregular seasonal patterns during the observed months. Sudden shifts, especially between Rainy and Cold or Hot and Warm, suggest unstable climatic behavior. Overall, the prediction reflects a dynamic weather trend with no prolonged dominance of any single category.

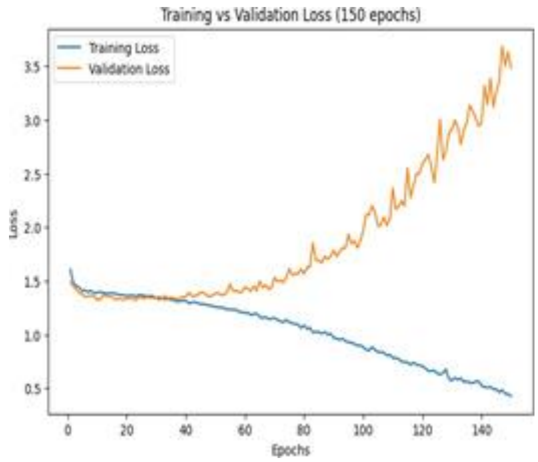


Figure 5.3 Prediction for the year 2025

The graph illustrates the training and validation loss over 150 epochs. Training loss consistently decreases, indicating that the model is learning effectively on the training dataset. In contrast, validation loss begins to diverge and increases significantly after approximately 40 epochs, suggesting overfitting. This behavior shows that the model generalizes poorly beyond this point, highlighting the need for regularization or early stopping.

5.1 CONCLUSION

This research focused on the application of deep learning models for weather classification in open farming and polyforming environments. The Attention-based LSTM model established a new benchmark for weather classification, outperforming all other architectures by a significant margin. The incorporation of an attention mechanism allowed the model to dynamically focus on the most critical weather patterns, leading to superior accuracy (98%) and generalization. BiLSTM and LSTM models also showed significant improvements over DNN and RNN architectures, especially in capturing sequential and temporal dependencies. This progression highlights the importance of advanced techniques such as attention mechanisms in improving model performance in time-series classification tasks.

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