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Managing Climate-Change Impacts through Predictive Analytics and AI-Driven Automated Irrigation

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Abstract: Climate change poses a major challenge to the agricultural sector because it disrupts weather patterns and reduces water availability. Effective irrigation-water management and accurate climate prediction are essential for mitigating these effects and supporting sustainable farming. This study analyzes the combined use of convolutional neural networks (CNNs) and artificial intelligence (AI) to predict future climate variations and automate irrigation. The proposed system uses a CNN to analyze historical climate data, satellite imagery, and weather forecasts and to generate accurate regional climate predictions. These forecasts are then supplied to an AI-based irrigation system that allocates water according to predicted weather conditions, soil-moisture levels, and crop requirements. The AI system uses real-time sensor data and dynamically adjusts irrigation schedules to improve water-use efficiency and minimize waste. Experimental findings indicate that integrating CNN-based prediction with AI-driven control can improve water management under farming conditions by providing farmers with insight into climate variability and an automated mechanism for reducing water loss. The approach demonstrates a sustainable and scalable method for improving agricultural productivity while mitigating climate-change risks.

Keywords: Climate Change, CNN, Artificial Intelligence, Irrigation, Automated Farming

1. Introduction

Agriculture is a key sector in the economic growth of many countries, especially those in which it serves as the backbone of the economy since it offers employment, food and raw materials to the industries [1]. However, simultaneously, the sector is subject to the increasing impacts of global warming, including extreme weather, rainfall deficits, and prolonged drought. Such interferences jeopardize the agricultural productivity and the food security of regions dependent on rain-fed or water-intensive farming. Also, the increasing world population and the shift in dietary habits are demanding even more agricultural products, thus increasing the pressure on an already limited supply of water resources [2].

Water scarcity is one of the greatest problems in agriculture currently. Agriculture is estimated to account for approximately 70% of global freshwater withdrawals and with the water resources over-strained due to climate change, inefficient irrigation practices are contributing to the wastage of freshwater [3, 4]. Improper irrigation practices and excessive irrigation cause the wastage of valuable water resources and poor irrigation systems also lack adaptive irrigation strategies, which translates into poor crop production. It is therefore necessary to address sources of water scarcity in agricultural production so as to provide sustainable food production and reduce the adverse financial outcomes in the agricultural economy.

The recent advancements in precision farming show the need to combine digital technologies with irrigation systems. Precision agriculture relies on sensors, IoT devices, wireless communication systems, remote sensing technology, and intelligent data analysis to track, manage, and optimize crop conditions and inputs. They give continuous information on the soil moisture, soil temperature, humidity, rainfall and crop health which helps farmers to make informed irrigation decisions. While they have enhanced resource use, many of the current irrigation systems are still based on threshold management systems that are inadequate to the task of responding to the rapid changes in climate. Thus, the development of intelligent systems that can learn complex environmental patterns and can adapt the irrigation schedules for dynamic field conditions is still in great need [5].

Climate change has exacerbated the complexity surrounding water use on farms. Climate change has added significant variability in temperature, precipitation, heat waves, and extreme weather events, adding to the uncertainty in farming operations. Most methods of irrigation scheduling are based on historical climatic averages and are insensitive to actual conditions. There has been a recent focus on the need for climate-smart agriculture to integrate weather forecasting, environmental monitoring data, and predictive analytics to enable predictive decision-making. These can help a lot in making systems more resilient to climate hazards, and increasing the efficiency of water use and crop production [6, 7].

In order to address these problems AI and CNN may provide a motivational resolution because they are advanced technologies. The potential of AI in processing large load of agricultural information, anticipating weather conditions, and optimization of resources has been enormous [8]. In the meantime CNN as a type of deep learning model, proves to be effective at computing and editing complex datasets of large volumes like satellite imaging and weather information. With the use of CNNs, we would be able to predict effects of climate change with higher precision and give farmers practical advice to change their behavior [9].

In recent years, AI has become a game-changer in the field of smart agriculture. Various machine learning and deep learning algorithms have been used to predict crop yields, detect diseases, identify weeds, optimise irrigation, and forecast climate conditions. In these approaches, CNNs have been widely studied for their potential to represent the intricate spatial and temporal structure and characteristics of heterogeneous agricultural datasets. CNN-based models have been shown to outperform traditional machine-learning algorithms on the analysis of satellite imagery, meteorological data, and environmental sensing data. In complex agricultural environments, CNNs can automatically extract relevant features, which alleviates the need for manual feature engineering and enhances prediction accuracy [10, 11].

Recent research has investigated the integration of sensor networks and predictive analytics to create AI-powered irrigation systems. These systems use real-time soil moisture, temperature, humidity and weather-forecast measurements to calculate irrigation needs. While some existing solutions are reported to be successful, most solutions are mainly aimed at irrigation automation ignoring the role of climate change prediction in the decision-making process. Likewise, climate prediction models are usually not integrated with irrigation management frameworks, and therefore, are not immediately usable in precision agriculture. This separation between climate forecasting and irrigation control is a major constraint of existing smart farming systems [12].

Moreover, automated irrigation can be transformed through the use of AI. By analyzing real-time data from soil sensors, weather forecasts, and other environmental factors, AI can dynamically decide water management and thereby achieve effective and sustainable irrigation [13]. This reduces water waste and enhances crop production while addressing the challenges of water scarcity and agricultural output.

While AI has made significant strides in agriculture, there are still several research challenges that have not been addressed. First, many irrigation management systems use rule-based or shallow machine-learning methods that are less flexible in adapting to changing climate conditions. Second, climate prediction studies already conducted often focus on the accuracy of the predictions but do not translate into the recommendations for irrigation. Third, the majority of existing smart farming technologies are directed towards single functions of agriculture, not towards an integrated solution that could deal with the three key aspects, namely climate prediction, water conservation and irrigation automation. The lack of comprehensive decision-support tools that can effectively close the gap between climate intelligence and irrigation management tools is a common problem experienced by farmers [14, 15].

In addition, the increasing volume of agricultural big data collected from various IoT sensors, weather stations and remote sensing technologies opens up possibilities for more advanced intelligent agriculture systems. But meaningful insights from these diverse data sources is a major challenge [16]. Due to their ability to handle large-scale multidimensional data and uncover relationships among environmental variables, deep-learning models, especially CNN architectures, hold promise to deal with big data. CNN-based deep-learning models have the potential to process large-scale multidimensional data and reveal hidden relationships among environmental variables. The combination of these features with AI-driven irrigation control systems can help predict climate-related impacts with greater precision and help implement adaptive water management practices, which can be implemented in real time.

Hence, there is a need for an integrated climate-smart irrigation solution which includes improved climate prediction and smart irrigation decision-making. This can help in achieving sustainable agriculture by minimizing water waste, optimizing irrigation water use, boosting crop productivity and resilience to climate variability. In water-stressed and climate-vulnerable regions, especially, the development of such integrated solutions is crucial for efficient use of limited resources for long-term food security and economic sustainability.

The proposed study introduces the possibility of integrating the approach to predicting climate change using CNN and a system of automatically irrigating water using AI to develop a finished system of modern farming. Using these technologies, farmers will be able to make accurate decisions based on the data, save water and enhance crop production, thereby making agriculture sustainable and support the economies of countries that rely on agricultural production. This approach would not only be effective in dealing with the short-term needs of water management, but it would also be effective in addressing the long-term effects of climate change on agricultural sustainability.

While there is considerable advancement in technologies for irrigation and climate-smart agriculture using artificial intelligence, the majority of the studies currently available focus either on climate prediction or on stand-alone irrigation automation. There is limited research on an integrated system that integrates CNN-based climate prediction with AI-based automated irrigation decision-making. The present study addresses this gap in research by integrating climate prediction, based on CNN, with automated irrigation decision-making, based on AI.

2. Literature Survey

A study by Yousef, *et al.,* (2024) in [17] examined how ML algorithms can be used to predict a very important parameter in reference evapotranspiration (ETo), that is, an element of efficient management of irrigation water. It evaluated the reliability and accuracy of numerous ML algorithms: Support Vector Regression, Random Forest, XGBoost, K-Nearest Neighbor, Decision Trees, Linear Regression and Multiple Linear Regression. The study made a comparative analysis of three methods of calculating ETo, which include Penman-Monteith, Hargreaves, and Blaney-Criddle calculations. As shown in the findings, the ML models can reliably predict ETo values, thereby giving an alternative to the traditional method of predictions.

The study by Park, and Lee, (2020) in [18] assesses the risk flooding will pose to the coastal regions of South Korea and compares it using different machine-learning algorithms. The study aims to forecast flood prone regions, thus an issue that has not been explored fully before. The research predicts the frequency of flooding in various climate-change conditions and sea level rise. A probabilistic risk map was generated, and there were values between 0 and 1, which illustrated the probability of occurrence of compound events, such as high tides and heavy rainfall. K-Nearest Neighbor algorithm achieved an accuracy of 0.946. The research observed that the southern coastal areas are more susceptible to flooding than the eastern and western ones and that the risk of floods is likely to rise steeply between the 2030s and the 2080s. It also emphasises that a probabilistic assessment methodology is useful to analyse coastal flood risk and assist in integrated coastal zone management decision-making.

Karthikeyana, (2021) in [19] criticizes the failure of the simulation model of a panel of experts on climate change (Intergovernmental Panel on Climate Change - IPCC), especially regarding the failure of a component within the Community Climate System Model (CCSM4) the Parallel Ocean Program (POP2). Such crashes take place when quantifying the effects of ocean model uncertain parameters when carrying out ensembles of uncertainty quantification (UQ). The paper provides the comparisons of different ML algorithms, e. g., Random Forest (RF), Linear Regression (LR), K-means, Naïve Bayes (NB) and the Support Vector Machine (SVM) classification is applied to predict and estimate the probability of the failure of simulations depending on the values of POP2 parameters. The method is also able to predict and quantify the failures, besides providing insight into the simulation crash on complex models in geo-scientific analysis.

The predictive methods applied in [20] by Bhuvana *et al.,* (2024) can also account for factors such as soil moisture and temperature, reducing the use of water and resulting in increased yields. Some algorithms in machine learning used to predict the water requirements are SVM, RF, Stochastic Gradient Descent (SGD) NB and DT. Even more complex deep-learning models such as the Feed-Forward and the Long Short-Term Memory (LSTM) may also be useful. The neural networks can be effective for prediction, however, the machine learning models applied in prediction making, including the RF and the DT are more efficient in providing timely predictions. Comparing performance using measures of accuracy, recall, precision, F1 score, and time of execution can aid in measuring and optimizing automated irrigation activities.

In [21], Anitha *et al.*, (2023) developed an IoT-based solar irrigation system, which was combined with the Artificial Neural Network (ANN) algorithms to ensure effective utilisation of water in agriculture. The system makes irrigation automatic, enhances production and minimizes the use of water. It involves solar panels, a water pump, storage tank, sensors, IoT and ANN algorithms. The water pump is managed by the system depending on the information obtained by the sensors, which automates the irrigation process to have the possibility to control water more efficiently.

In [22], Kalpana, *et al.,* (2024), the following review of the systematic literature examines the latest developments and issues of the traditional irrigation system that is supplemented with the IoT and machine-learning algorithms. Examining 43 articles between 2017 and 2024, the review demonstrates how these technologies are now being developed to deal with the current issues in the field of agricultural irrigation. It underscores the application of predictive analytics, anomaly detection, and adaptive control with the aim of enhancing irrigation accuracy and decision-making. Using PRISMA approach as a review tool, the strong points identified in terms of using real-time data and system responsiveness are noted, and issues such as complexity of data integration, network reliability, and scalability have also been identified. It identifies gaps in standardization and necessity of flexible approaches to a wide variety of environmental circumstances that may provide ideas in the development of smart irrigation technologies and the necessity of additional research that can solve the existing barriers to the widespread implementation.

The study by Akanbi, (2025) in [23] outlines the use of an AI-powered system in solar irrigation in the context of a sustainable approach to ensure that the use of water is optimized alongside the agricultural productivity. The system uses machine learning programs, IoT-based soil moisture sensors, and real-time weather forecasting to automate irrigation, adjusting schedules according to soil moisture, the weather, and crop water requirements, reducing water wastage and maximizing profit. Use of solar energy reduces fossil-fuel use, lowers costs, and improves environmental sustainability. A case study of Nigeria shows how the system has been successful in enhancing crop yield and conservation by reducing water consumption as well as efficiency improvement in the energy sector. Although AI-assisted irrigation has a lot of advantages in precision farming, some of the issues that need to be resolved before widespread implementation are high start-up costs, absorption, and maintenance. The paper recommends a need in focusing and investment in smart farming technology and the support of policies and collaboration to achieve the complete potential of AI-based irrigation in sustainable agriculture. The detailed survey related to the proposed work is presented in summarized form in Table 1.

Table 1. Summary of the Literature Survey

Author/Year	Data Type	Method	Application Focus	Key Findings
Yousef *et al.* (2024) [17]	Meteorological and environmental data	SVR, RF, XGBoost, KNN, DT, LR, MLR	Reference Evapotranspiration (ETo) Prediction	ML models accurately predicted ETo and provided alternatives to conventional estimation methods.
Park & Lee (2020) [18]	Climate, sea-level, and rainfall data	K-Nearest Neighbor (KNN)	Coastal Flood Risk Prediction	Achieved 94.6% accuracy and identified high-risk coastal flood zones under climate change scenarios.
Karthikeyana (2021) [19]	Climate simulation parameters	RF, LR, K-Means, NB, SVM	Climate Model Failure Prediction	Successfully predicted simulation failures and quantified uncertainty in climate models.
Bhuvana *et al.* (2024) [20]	Soil moisture and temperature data	SVM, RF, SGD, NB, DT, LSTM	Irrigation Water Requirement Prediction	Improved irrigation scheduling using environmental parameters and machine-learning algorithms.
Anitha *et al.* (2023) [21]	IoT sensor data	ANN + IoT	Solar-Powered Smart Irrigation	Automated irrigation improved water efficiency and crop productivity.
Kalpana (2024) [22]	Literature Review (2017–2024)	IoT and ML-based Irrigation Systems	Smart Irrigation Review	Identified benefits of predictive analytics and adaptive irrigation control
Akanbi (2025) [23]	Soil moisture, weather, and IoT data	AI + Machine Learning + IoT	Solar Irrigation Management	Reduced water consumption and improved crop yield through AI-assisted irrigation
Proposed Work (2025)	Images + Sensor Data + Weather Data	CNN-Based Climate-Aware Irrigation Framework	Climate Prediction and Smart Irrigation	Achieved 91.3% accuracy through multimodal data integration and intelligent irrigation decision support.

From the above literature survey the following research gaps were identified:

- Reliance on Threshold-Based Irrigation- The majority of current IoT irrigation systems are based on predefined soil moisture thresholds, which are not capable of responding effectively to environmental and crop variations.
- Minimal Multimodal Integration- Earlier research is predominantly sensor-oriented numerical data and is not integrated into a single framework that incorporates visual crops, environmental sensing, and statistical analysis of climate.
- Weak Crop Stress Pattern Detection - The conventional machine-learning systems cannot identify more complex visual patterns such as leaf discoloration, wilting, and textural variation in the soil, and other drought symptoms which influence irrigation requirements.
- Absence of Intelligent Decision Support - Existing irrigation systems tend to provide automated control but do not provide explainable, adaptive, and
- Data-driven decision-making to control irrigation in a precise manner.

The proposed work has the following objectives:

- Create a climate-change forecasting framework based on CNNs and AI.
- Predict weather conditions and how it will affect the demand of water as an irrigation process.
- Create a irrigation system with automated irrigation that is smart enough to optimize the usage of water due to climate forecasts, farm conditions and soil conditions.
- Contribute to water saving and agricultural efficiency by leveraging the AI-based predictions and automation.
- Advanced Visual Feature Learning Use a CNN to automatically capture rich spatial information of crop and soil images, including moisture patterns, crop stress, leaf discoloration, and soil texture variations that cannot be effectively modeled with conventional models.
- Enhanced Intelligent Decision-Making - Implement a CNN to improve accuracy in predicting irrigation by utilizing the image-based analysis and sensor measurements, and make adaptive and data-driven irrigation decisions to manage water more efficiently.

3. Proposed Work

This section presents the materials and methods adopted in the implementation of the proposed system of monitoring the climate with particular emphasis on cost-effectiveness and water resource efficiency. As the quantity of water involved in irrigation is a very vital factor, the system should minimize water use while maximizing agricultural potential and crop production. The system will be a continuous integration of the soil moisture, temperature and humidity measurements of the IoT sensors and historical irrigation schedules and crop requirements.

3.1 System Architecture

The proposed smart irrigation system operates as an autonomous closed-loop irrigation management system that monitors field conditions, evaluates irrigation requirements and automatically responds with limited user intervention. The monitoring, processing, communication and actuation units are self-powered by renewable energy sources, enabling sustainable operation in remote agricultural settings. The monitoring devices collect and send data to the processing unit, which has the control logic to assess field conditions against operational irrigation needs and to determine the appropriate action. When irrigation is needed, the actuation unit is activated to precisely control water delivery based on crop requirements, while the feedback loop ensures timely irrigation when optimal conditions are met.

At the same time, operational information is shared with the mobile app-based platform, allowing remote monitoring, scheduling, and system supervision, and real-time notifications of system status or fault conditions. The integration of automated decision-making, real-time communication and remote accessibility in a single platform enables the proposed work to offer accurate irrigation control, enhance resource efficiency, simplify the irrigation process and promote sustainable crop productivity. Figure 1 shows the architecture of proposed work.

3.2 Hardware Components

The proposed automatic irrigation system is based on the interaction of various components, all of which help to manage water consumption, reduce labour costs, and promote healthy plant growth. Figure 2 shows the Hardware components involved in the proposed system. The solar panel is the central component of the system, as it acts as an energy source, converting sunlight into electricity. This clean energy is harnessed to power the control system, sensors, and motor, with any remaining power stored in a battery for operation on overcast days or during the night. To complement this, the solar charger box and battery management circuit manage charging, over-charging and under-charging, and maintain a consistent energy supply for the ongoing operation of the irrigation system.

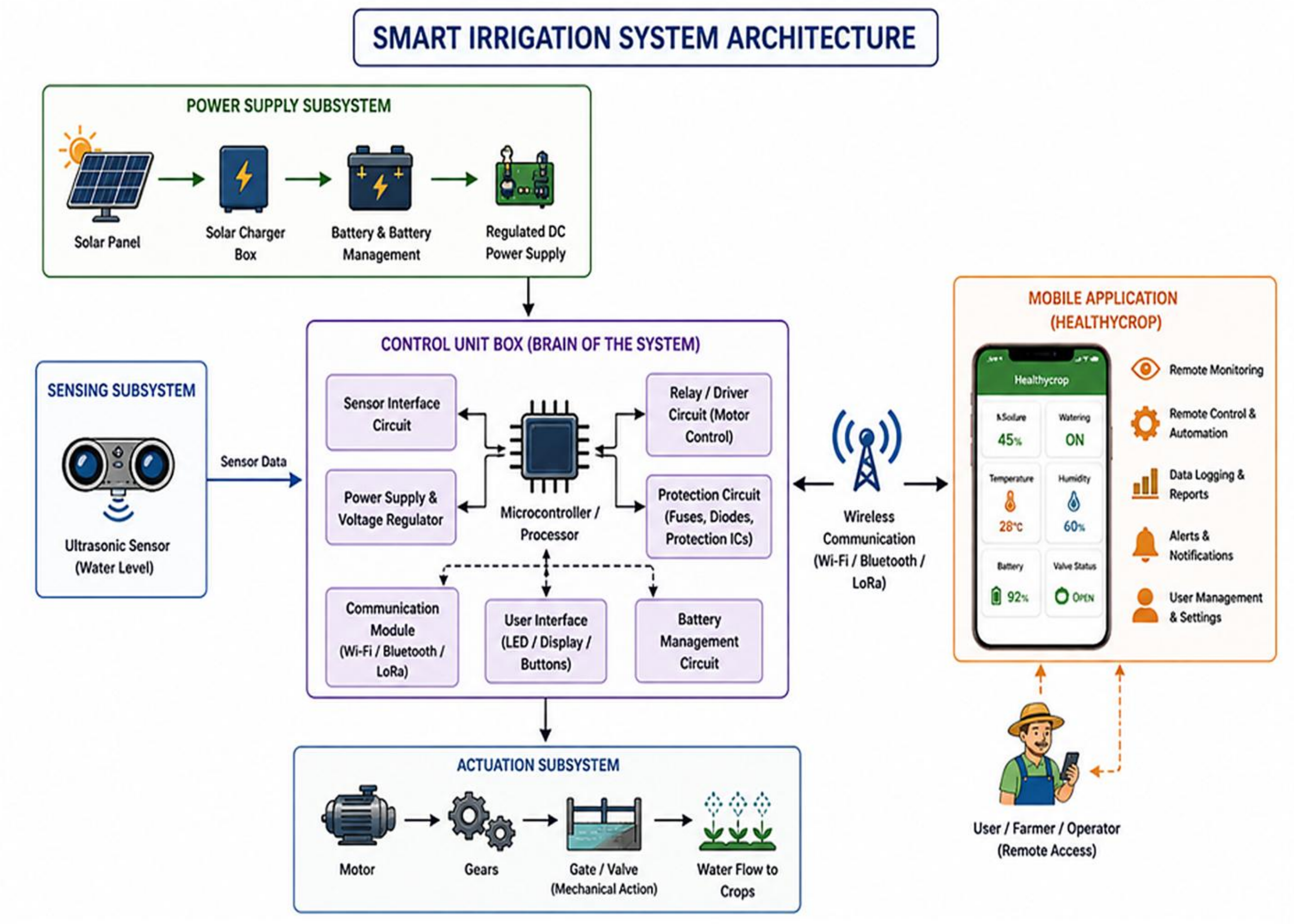

Figure 1. System Architecture of the Proposed Work.

The control unit box is the central decision-making unit of the irrigation system, which receives signals from sensors. Within the box, a microcontroller/processor receives signals from sensors, particularly the ultrasonic sensor, and decides when to irrigate based on certain criteria. The power supply and voltage regulator regulate power levels to ensure a steady voltage supply to sensitive electronic parts and maintain system stability and reliability. Moreover, the sensor interface circuit is used to condition signals from sensors to be suitable for the microcontroller, and the relay/driver circuit is used to amplify the control signals from the microcontroller to drive high-power devices like motors. The protection circuits, such as diodes and fuses, protect the entire system from electrical issues, including overvoltage, overheating and short circuits, and increase the system's reliability and lifespan.

The motor-and-gear assembly is responsible for physically executing irrigation. When the control unit identifies the need for irrigation, it activates the motor to rotate, which in turn transfers power via the gears to open or close the irrigation valves or gates. The gearing system provides the necessary torque, speed reduction and mechanical positioning to control the water flow. This automation reduces manual labour and guarantees irrigation as required by the plants.

The ultrasonic sensor is a monitoring element that determines the water level or the distance to the water surface based on reflected sound waves. The sensor uses the time of flight of the sound waves to calculate the water level and feeds this data to the control unit for decision-making. The metal plate is a component either used as a reflective element to improve the accuracy of the ultrasonic sensor or part of the valve/gate mechanical structure operated by the motor and gears. In some smart irrigation systems, the communication module (Wi-Fi, Bluetooth, LoRa) adds an additional layer of smartness by facilitating remote monitoring and control from a mobile device or computer, enabling farmers to monitor water levels, control irrigation scheduling and assess system performance remotely. These hardware components are incorporated into a smart irrigation system, achieving water conservation, efficiency and productivity enhancements.

3.3 Software Components

The proposed automatic irrigation system architecture needs software components, shown in Figure 3, and uses a mobile software application, as its primary software to enable smart monitoring, remote operation and automation of irrigation tasks.

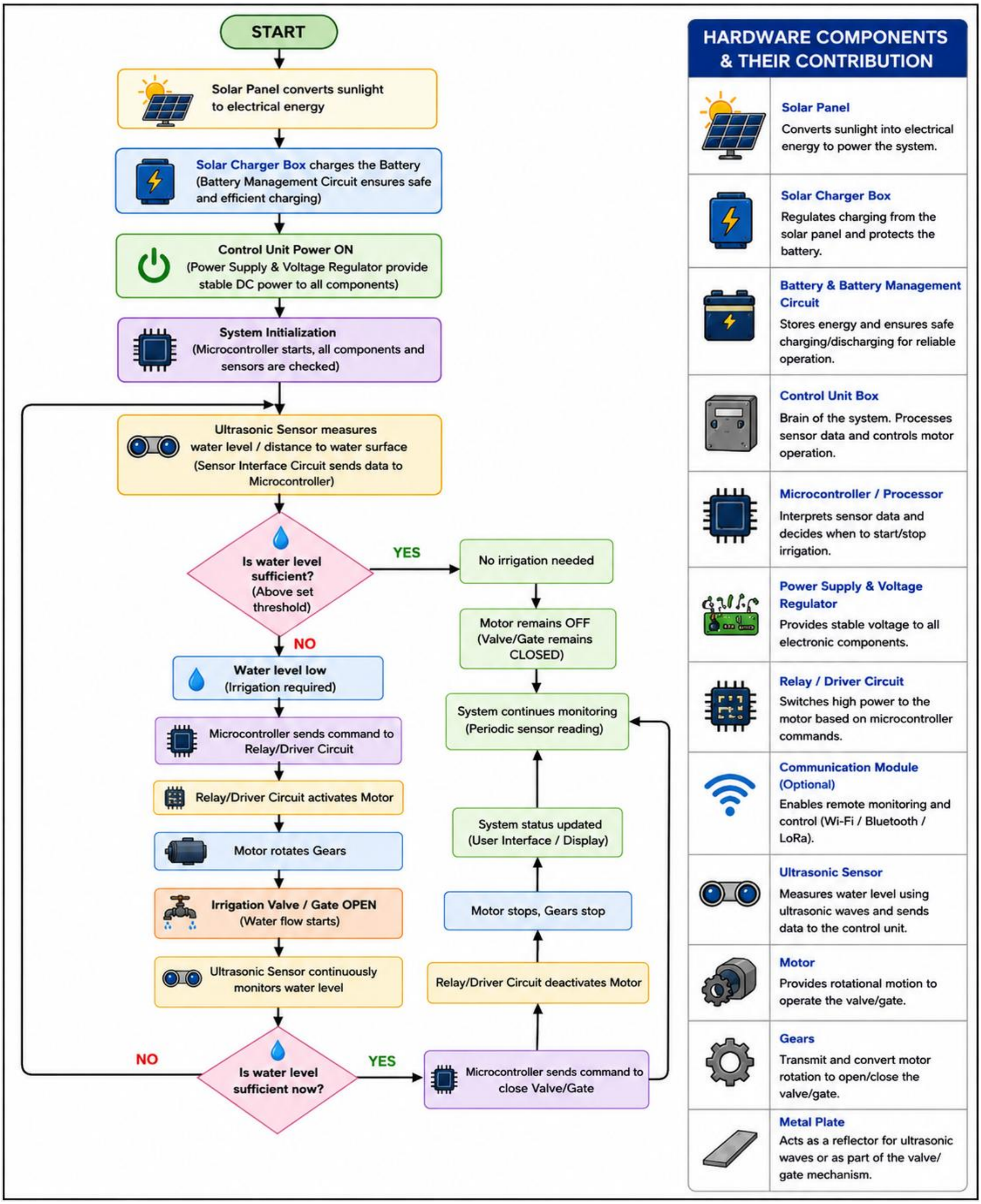

Figure 2. Architecture of the Hardware Components.

The software provides a simple interface which enables farmers and system managers to remotely monitor the irrigation system via mobile devices (smartphone, tablet), enabling them to manage the farm from anywhere. The software features a user-friendly interface, easy-to-understand menus, and touchscreen controls to ensure easy use by users with little technical background. The software communicates with sensors in the field and provides real-time data such as soil moisture, watering status, environmental conditions (temperature, humidity, and solar radiation) and overall system performance (pump status, valve status and battery status) to allow the user to track the status and efficiency of the irrigation system at any time.

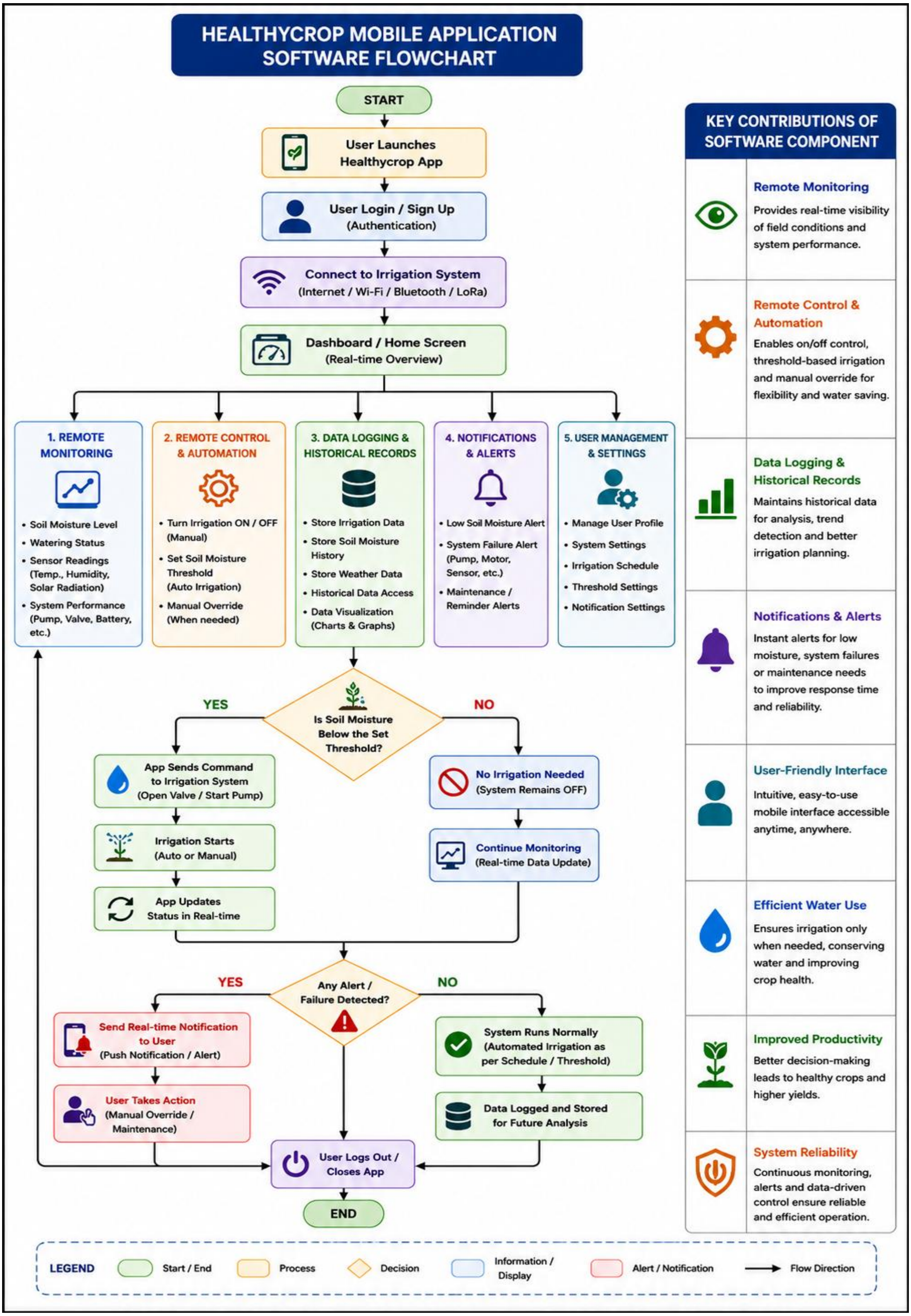

Figure 3. Architecture of the Software Components.

The software component plays a major role in the effectiveness of the proposed work as it allows remote monitoring, intelligent automation, and data management, as well as real-time communication between the system and the user. It allows automated irrigation based on preset soil moisture thresholds, ensuring crops receive water only when necessary, which improves water conservation and crop health. At the same time, users can manually override automated operations whenever special conditions require direct intervention. The software also stores historical records of irrigation cycles, soil moisture patterns, and weather-related data, which helps in analyzing long-term trends and improving irrigation planning through data-driven decision-making. Additionally, real-time alerts and notifications regarding low soil moisture, system malfunctions, maintenance reminders, or unexpected operational issues improve responsiveness and system reliability. Overall, the Healthycrop mobile application acts as the intelligent software backbone of the proposed irrigation system, enhancing automation, operational efficiency, accessibility, and decision-making while reducing manual effort and resource wastage.

3.4 Data Acquisition

The experimental field was 1 ha in area, and under the cultivation of coconut crop. The study was carried out in the city of Thanjavur, in Tamil Nadu, India (lat. 10.7870° N and long. 79.1378° E) which is a tropical monsoon region with seasonal rainfall and plenty of agricultural activities. All the 10 sensors (soil moisture, soil temperature, air temperature, humidity, rainfall, and water-level sensors) were installed in the field to keep a continuous check on the environment.

During the one-year monitoring period from January 2024 to January 2025, 105,120 time-stamped measurements were taken by sensors at 5-minute intervals. In total, there were 1051200 individual sensor readings, when taking all deployed sensors into account. Data with missing values due to temporary communication interruptions and sensor interruptions were processed using linear interpolation and mean-value imputation technique, and the outliers were statistically filtered. All the sensor data, weather data and field images were stored in a centralized time-series database for further analysis and prediction of climate indicators using CNN. The complete dataset was split into training (70%), validation (15%) and testing (15%) subsets, which were used to ensure reliable performance evaluation and generalization capability when developing the model. The parameters used in the dataset are shown in Table 2 while a sample of the data collected for this study is shown in Table 3 as sample.

3.5 Model Work Flow

Integrating CNNs into dynamic irrigation improves the analysis and predictions of the system of irrigation demand due to patterns in the sensor data and weather conditions. The decision-making process can be enhanced, making the system more adaptable and scheduling irrigation practices using current data and complicated trends using CNNs. The proposed CNN architecture in Figure 4 is a multi-level deep feature learning model that converts agricultural images to usable insights for smart irrigation management and climate forecasting. The model contains the following layers:

3.5.1 Input Layer (224 × 224 × 3 RGB Image)

Agricultural images such as crop leaves, soil images and field images are the main source of data for the CNN model, and are fed into the input layer. It conducts image preprocessing and normalization to ensure image quality and size consistency for effective processing. This is the starting point for feature extraction, allowing the model to learn relevant agricultural features for smart irrigation.

Table 2. Dataset Parameters

Column Name	Data Type	Description
Sensor_ID	VARCHAR	Unique identifier for each sensor
Timestamp	DATETIME	Date and time of data collection
Soil_Moisture (%)	DECIMAL	Soil moisture level as a percentage
Soil_Temperature (°C)	DECIMAL	Temperature of the soil at the sensor location
Air_Temperature (°C)	DECIMAL	Air temperature near the sensor
Humidity (%)	DECIMAL	Relative humidity near the sensor
Irrigation_Status	BOOLEAN	Whether irrigation is ON or OFF

Table 3. Sample Dataset

Sensor_ID	Timestamp	Soil Moisture (%)	Soil Temp (.C)	Air Temp (.C)	Humidity	GPS Lattitude	GPS Longitude	Irrigation Status	Rainfall (mm)	Wind Speed(km/h)	Sunlight
S001	3/25/2025 8:00	28.5	23.1	26.5	65	28.6139	77.209	FALSE	0	5	55000
S002	3/25/2025 8:00	31.2	22.7	25.8	68	28.614	77.2091	FALSE	0	6	54000
S001	3/25/2025 10:00	24.1	24	28.2	60	28.6139	77.209	TRUE	0	7	58000
S002	3/25/2025 10:00	29.5	23.5	27	64	28.614	77.2091	FALSE	0	6	57000
S001	3/25/2025 12:00	35	26.5	30	58	28.6139	77.209	FALSE	0	10	60000
S002	3/25/2025 12:00	37.8	26	29.5	60	28.614	77.2091	FALSE	0	9	59000
S001	3/25/2025 14:00	40.2	27	31	55	28.6139	77.209	FALSE	0	12	62000
S002	3/25/2025 14:00	42	26.8	30.8	57	28.614	77.2091	FALSE	0	11	61000
S001	3/25/2025 16:00	45.5	28	32.5	50	28.6139	77.209	FALSE	0	14	63000
S002	3/25/2025 16:00	47.3	27.5	32	52	28.614	77.2091	FALSE	0	13	62000

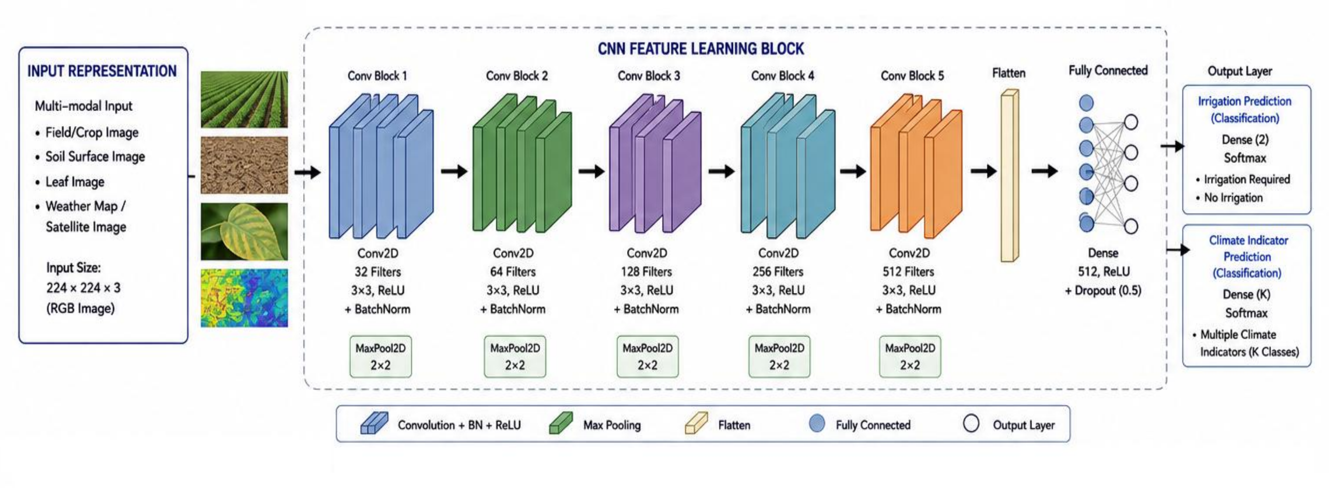

Figure 4. CNN Architecture for the Proposed Work.

3.5.2 Convolution Layer 1 (32 Filters, 3×3 Kernel, ReLU Activation)

The initial convolutional layer detects basic visual patterns like edges, contours, textures and changes in brightness in the farm images. It captures initial features of soil, leaf structures and moisture content that are visible in the image, serving as the first feature maps. ReLU activation function introduces non-linearity into the model that enables it to depict complex relationships between the images.

3.5.3 Batch Normalization

The batch-normalization layer standardizes feature values throughout the training process, and stabilizes the flow through the network. It accelerates learning and stabilises the network by minimising internal covariate shifts. This leads to a more accurate and stable model for various agricultural image conditions.

3.5.4 Max Pooling Layer (2×2)

The max pooling layer reduces the size of feature maps while preserving prominent visual patterns of farm images. It removes redundancies, lowers the number of parameters and increases speed. It also enhances robustness to scale and translation of feature maps and retains main moisture and crop health patterns for prediction.

3.5.5 Convolution Layer 2 (64 Filters, 3×3 Kernel, ReLU Activation)

The second convolutional layer acquires the patterns on intermediate levels based on the basic features that have been acquired in the previous layers of the network. It detects critical visual variations including wet and dry soil texture, discoloration of leaves, areas of stress and surface anomalies. This makes the model more reliable in distinguishing the healthy crops and those in stress or water deficiency.

3.5.6 Convolution Layer 3 (128 Filters, 3×3 Kernel, ReLU Activation)

The third convolutional layer learns more intricate spatial patterns and feature combinations in agricultural images. It understands water content patterns, growth patterns and visual symptoms of environmental stress like yellowing or wilting. This enhances the ability to discern crop conditions and improves the model's predictive capability for precision irrigation

3.5.7 Convolution Layer 4 (256 Filters, 3×3 Kernel, ReLU Activation)

The fourth convolutional level acquires high-level semantic features about agricultural conditions using intricate patterns in the images. It records the symptoms of disease, drought stress, and changes in vegetation density, which affects the health of crops. This enhances the capability of the model to differentiate irrigation demands besides aiding in analyzing climate-related features.

3.5.8 Convolution Layer 5 (512 Filters, 3×3 Kernel, ReLU Activation)

The fifth convolutional layer learns abstract and discriminative features of agricultural images for further processing. This layer captures intricate interactions between crop features, soil properties, and other stress factors that influence irrigation needs. This feature representation leads to more accurate decisions and robust predictions in various agricultural contexts.

3.5.9 Flatten Layer

The flatten layer converts feature maps into a feature vector for further processing. It translates learned spatial features to a small vector for dense layers. It serves as a bridge between deep feature extraction and classification in CNN models.

3.5.10 Fully Connected Dense Layer (512 Units, ReLU)

The fully connected dense layer receives the extracted features and integrates them into higher-level meaningful patterns to be intelligently analyzed. It also acquires the correlation between crop visual characteristics, irrigation needs, and climate cues. This enhances the decision-making ability of the CNN and increases the classification accuracy for smart-irrigation management.

3.5.11 Dropout Layer (0.5)

The dropout layer randomly turns off selected neurons during training to make the learning less reliant on particular features. This will avoid overfitting and enable the model to learn more generalized patterns by using agricultural data. Consequently, it enhances the predictive reliability and performance on unseen field conditions that occur in reality.

3.5.12 Output Layer – Irrigation Prediction (Dense + Softmax)

The irrigation prediction output layer produces the final decision on whether irrigation will be implemented based on probabilities. It categorizes the crop water requirements accurately according to the learned visual and environmental characteristics. This allows automatic irrigation control and enhances efficiency of water use with intelligent prediction.

3.5.13 OutputLayer – Climate Indicator Prediction (Dense + Softmax)

The climate indicator output layer forecasts the environmental and climate-related agricultural situations that determine the irrigation planning. It categorizes the effects of weather and assists in adaptive scheduling depending on the alterations in the field conditions. This enables optimization of the management of water by determining the irrigation decisions based on climate patterns and crop demands.

3.5.14 Optimizer (Adam)

Adam optimizer is an efficient algorithm used to update model weights when training with adaptive learning mechanisms. It enhances learning stability, speeds up convergence, and allows large agricultural datasets to be learned effectively. This leads to a better model accuracy and trustworthy prediction behaviour of the smart irrigation applications.

3.5.15 Loss Function: Categorical Cross-Entropy

During the training of a model, the loss function measures the difference between actual outputs and predicted classes. It helps the CNN reduce classification errors through effective adjustment of network parameters. This enhances the accuracy of irrigation prediction and robust performance in climate-related classification.

3.5.16 Regularization (L2 Weight Decay)

The regularization layer discourages overly complex model weights, allowing the network to avoid relying on particular training patterns. It makes the model less sensitive to noise, and better predicts the unseen agricultural data. This improves the stability of predictions and it helps in the consistent deployment even in real-world agricultural settings.

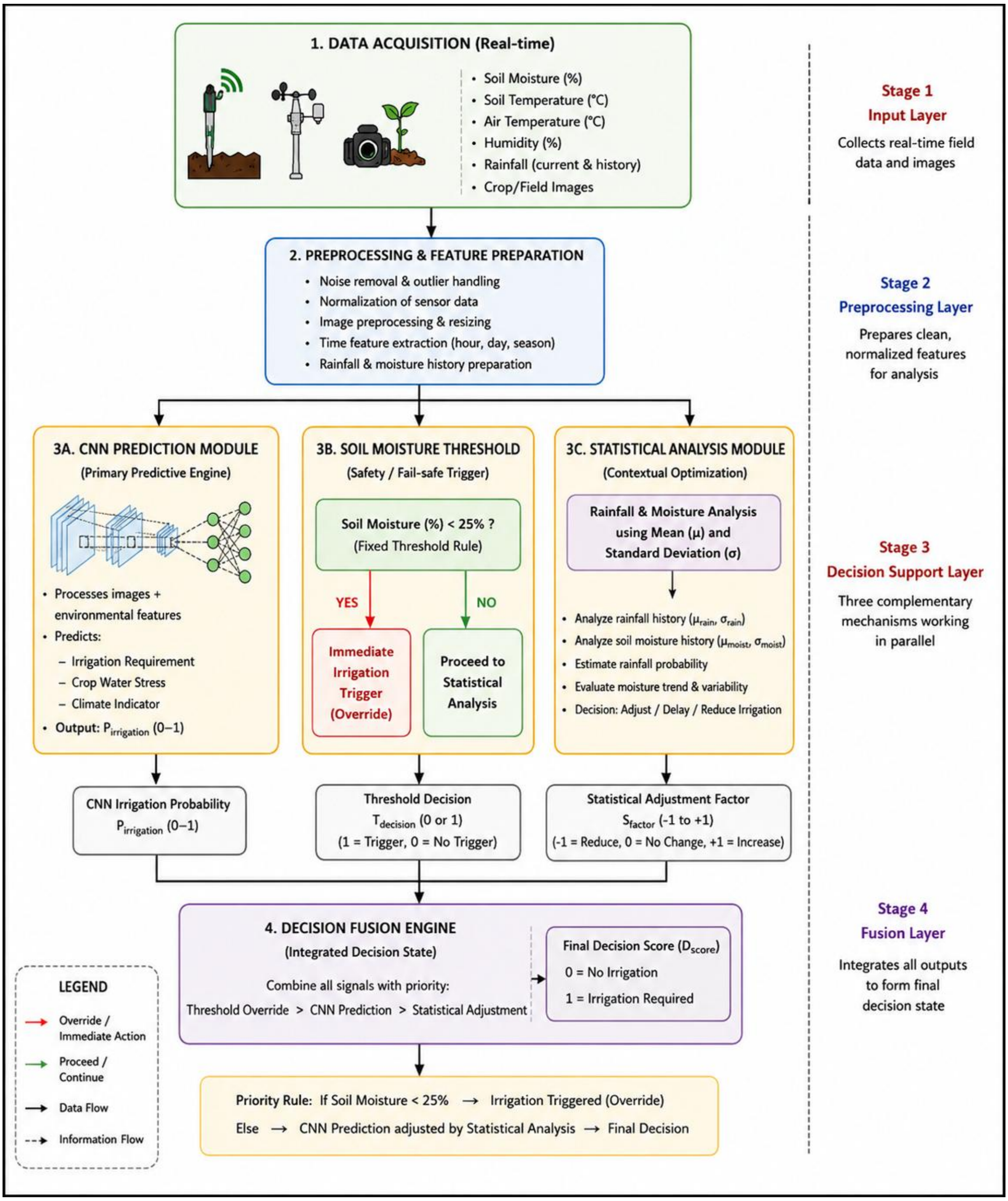

Figure 5. Multimodal Data integration Layout of Proposed Work.

Table 4. Hyperparameters

Training Hyper Parameters	
Optimizer	**Adam**
Learning Rate	0.001
Batch Size	32
Loss Function	Categorical Crossentropy
Regularization	Dropout (0.5) in Dense Layer L2 weight Decay (1e-4)
Batch Normalization	After each Conv Layer
Epochs	100
Learning Rate Scheduler	ReduceLROnPlateau (Factor=0.5, patience=5, min_lr=1e-6
Implementation	Python, tensorFlow/keras

The provided flowchart of the given system in Figure 5 based on the decision-making rule is used for irrigation management, considering first the soil moisture conditions and then the volume of precipitation. It starts with an assessment of the existing moisture value in the soil. When the moisture level is below the defined threshold (here 2 is the standard deviation and the mean is denoted by mu 2) (mu-sigma), then it will validate whether the recent precipitation is more than 2 mm. Otherwise, it activates irrigation (Irrigation: ON); when there is enough rainfall, it leaves irrigation switched off. When the moisture of the soil is not less than 2/Rms, it tests whether it is lower than 2/Rms. provided it is, then the system switches irrigation to the OFF state, under the assumption that moisture is within reasonable limits. One more protection is implemented: when moisture is below 2-sigma, irrigation is turned off, otherwise it sends an "Irrigation ALERT", that there has been an abnormally dry condition that needs to be taken care of. The system will concludes that no adjustment is necessary when soil moisture is more than 20 but3 in frequency. In general, this flowchart provides a statistical threshold to make an irrigation decision dynamically and automatically that addresses both, water conservation and the health of the soil. Table 4 shows the hyperparameters used for this work.

The suggested smart irrigation system is based on a hierarchical multi-stage inference chain in which the CNN model, threshold-based control logic, and statistical rainfall-moisture analysis are used as interdependent decision-support layers and rather than as independent systems; the AI-based prompt system is the intelligent interpretation and recommendation layer. The first level involves the collection of real-time field data, e. g., soil moisture, soil temperature, air temperature, humidity, rainfall history, and crop images, via sensors and imaging devices. CNN model serves as the main predictive engine, which takes the image-based crop and soil conditions, along with environmental inputs, to classify crop water stress, predict irrigation demand, and forecast climate-related conditions with a high accuracy. The fixed soil moisture rule (25%) serves as an operational validation and safety cue at the second level where irrigation is automatically switched on when the moisture drops to the predetermined threshold irrespective of predictive outputs, keeping crops safe due to under-irrigation by abnormal field conditions. The third step is a statistical analysis of rainfall and moisture data (mean and standard deviation) that assesses the past weather conditions, probability of rainfall and moisture variability to decide whether the forecasted irrigation demand needs to be revised, postponed or minimized to prevent unnecessary watering in cases where natural precipitation is expected or moisture patterns in the soil are stable. Lastly, the products of the three layers are combined to form a single decision state and fed into the OpenAI-based prompt system that translates the aggregated analytical outputs, creates human understandable recommendations (including irrigation timing, water quantity adjustment, and climate advices) and disseminates them via the Healthycrop mobile application that informs farmers and enables remote control. The CNN production of the primary irrigation prediction, the activation of the threshold mechanism as a fail-safe, the contextual optimization of the statistical model, and the OpenAI transformation of machine decisions to interpretable and actionable agricultural intelligence, create a complete, intelligent, and adaptable irrigation decision-making pipeline in this architecture.

According to the given framework, climate-indicator prediction is not a binary classification or time-series forecasting issue, but a multiclass classification problem. This module aims to categorize the real-time environmental conditions into discrete irrigation-relevant climate categories, which affect the demand of crops to water. According to sensor measurements and weather observations, four classes were determined: Class 0 - Normal Condition (moderate temperature, balanced humidity and stable soil moisture), Class 1- Dry Condition (high temperature, low humidity, low rainfall probability and declining soil moisture), Class 2- Humid Condition (high humidity with moderate moisture retention and reduced evaporation), and Class 3- Stress

Condition (extreme heat, extreme moisture loss The rule-based annotation framework was created based on sensor streams (soil moisture, soil temperature, air temperature, humidity, rainfall statistics mean rainfall and standard deviation) to generate ground-truth labels based on sensor streams and short term weather observations. To illustrate, records that had air temperature exceeding 35 o C, humidity less than 40 per cent and soil moisture lower than the threshold were classified as Dry Condition whereas records with high humidity (>75 per cent), moderate temperature, and stable soil moisture were classified as Humid Condition. In the same way, extreme combinations that denoted crop stress were considered to be Stress Condition, and balanced environmental readings were considered to be Normal Condition. The resulting labeled dataset spread was composed of Normal (32%), Dry (28%), Humid (22%), and Stress (18%) so that there would be enough distribution of all the classes in the model training and evaluation. This class definition, annotation protocol and class distribution render the climate-indicator prediction scientifically measurable, reproducible, and apt to an effective classification analysis with CNN-based learning.

3.6 Multimodal Data Integration Framework

The proposed framework aims to make irrigation decision-making more reliable and robust by using a multi-modal decision-making support layer made up of three parallel processing modules. These modules use image data, information from IoT sensors and weather data to assess field conditions through complementary angles. The CNN module conducts predictive analysis, while the threshold-based module guarantees an urgent response when moisture conditions are critical. The statistical module is used to improve decisions based on historical environmental patterns. Details of the operation of each module are discussed in the following subsections. Figure 5 will provide information regarding the combination of multimodal input handle including CNN prediction module, Threshold for Soil moisture and Statistical Analysis Module.

3.6.1 3A-CNN Prediction Module

The CNN Prediction Module is the main intelligence part of the proposed smart irrigation system. This module is provided preprocessed field images and normalized environmental data such as soil moisture, soil temperature, air temperature, humidity, precipitation data etc. The convolutional layers automatically learn high level spatial features of the crop and field images and capture the information about the health of the vegetation, stress on the crop, soil information, moisture pattern, etc. These image-based features are fused with sensor and weather data by feature fusion and fed into fully connected layers to learn the complex relationships between environmental conditions and irrigation needs. The CNN is trained to classify whether a given image is an irrigated crop or not by trying to minimize the classification error with labelled agricultural images. Once trained, the model can be used in inference to give an irrigation probability score $P_{irrigation}$ between 0 and 1, representing the probability of irrigation being required in the field at the moment.

3.6.2 3B Soil Moisture Threshold Module

The Soil Moisture Threshold Module is a fail-safe tool that will help address critical water stress conditions at the first opportunity. In this module, the real-time soil moisture readings from the sensors attached to the IOT system are constantly monitored and compared with an expected value M_{th} = 25%. When the measured soil moisture M_t is less than this threshold, the system automatically starts irrigation, even if the CNN prediction results are not good. This override helps to avoid damages to the crop, even if irrigation timing is delayed, and ensures operation even in the case of unanticipated environmental conditions. Once the soil moisture reaches the threshold, Soil moisture monitoring is transferred to the Statistical Analysis Module and CNN-based decision making process for further analysis. The module produces a binary decision value, called $T_{decision}$, with the value 1 representing immediate irrigation, and the value 0 representing that further analysis is required.

The irrigation decision based on soil moisture is defined by Equation (1):

$$T_{decision} = \begin{cases} 1, if\ M_t < 25 \\ 0, if\ M_t \geq 25 \end{cases} \quad (1)$$

If $T_{decision} = 1$ Irrigation is triggered immediately and $T_{decision} = 0$ Irrigation is not triggered and further analysis is performed.

3.6.3 3C Statistical Analysis Module

The Statistical Analysis Module provides additional soil moisture and rainfall trends in the system to improve irrigation decision-making. This is not a predictive-learning module like the CNN module, but is a statistical evaluation module that uses indices like mean (μ) and standard deviation (σ) to investigate the variability of the environment and the availability of water in the future. Past precipitation data and moisture availability is analyzed to assess the likelihood of precipitation and if the requirement for irrigation can be met from a natural source of moisture. The module uses this analysis to calculate a statistical adjustment factor (S_factor) that can reduce, hold constant or improve the recommendation for irrigation made by the CNN model. This helps to reduce unnecessary water use, increase water use efficiency and better match the water use decision to current and predicted conditions.

All three parallel modules' outputs are combined in the Decision Fusion Engine. The Soil Moisture Threshold Module is evaluated first as it has the highest priority and is capable of overriding all other decisions should critical moisture deficiency be detected. When no override condition exists the irrigation probability generated by CNN is taken as a primary prediction. The Statistical Analysis Module then corrects this forecast with the adjustment factor that is calculated based on rainfall and moisture trend analysis. The combination of the resulting decision score gives the final irrigation decision, thus using the image-based prediction, real-time sensor measurement and weather information together in the training and deployment of the proposed system.

4. Result and Discussion

To evaluate performance of agricultural prediction, the proposed CNN model was compared to the RF, SVM and LR as they are among the most popular and widely accepted benchmark classifiers in the field of ML. LR was chosen as a baseline linear model because it is simple, interpretable and works well on binary and multiclass classification problems, and therefore a cornerstone of reference when trying to determine whether complex models can truly make a significant contribution. The SVM was selected due to its high classification capacity in nonlinear decision boundaries and its success in sensors used in agricultural monitoring, environmental classification, and predictive analytics with medium-sized datasets. RF was also added since it is a powerful ensemble learning algorithm that can address noisy sensor measurements, nonlinear interactions of features, and high-dimensional agricultural measurements and strong generalization capabilities. These three models combined comprise LR, nonlinear learning (SVM) using kernels, and the use of an ensemble of trees (RF), which provides a complete spectrum of benchmarks in which the proposed CNN-based deep learning architecture can be fairly judged. Such a comparison scientifically reveals whether the proposed model offers better feature learning, predictive accuracy, and robustness compared to the conventional machine learning methods in smart irrigation decision-making. The following quality analysis parameters were evaluated to analyse the performance:

- TP: True Positives (correctly predicted positive cases)
- TN: True Negatives (correctly predicted negative cases)
- FP: False Positives (incorrectly predicted positive cases)
- FN: False Negatives (incorrectly predicted negative cases)

Accuracy

Accuracy is a popular performance measure in classification. It is computed as the ratio of correct predictions made by a model to the total number of predictions and is calculated by using Equation (2)

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

Precision

Precision is a measure of performance associated with classification tasks, which is helpful for imbalanced datasets. It determines the accuracy of positive forecasts say, how many of the predicted positive cases are true by defining the Equation (3)

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

Recall

Sensitivity, or the true-positive rate (TPR), also called recall, is a primary metric of performance used in classification, and is usually important in real-world situations where a positive example is important to identify, as in disease detection, intrusion detection, or failure of irrigation control systems to (possibly remotely) alert the user. It can be obtained by using Equation (4)

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

F1-Score

The F1-Score is a measure of performance which combines precision and recall into a single value given in Equation (5). It is particularly applicable when balancing false positive and false negative particularly for skewed datasets.

$$F1 - Score = 2.\frac{Precision.Recall}{Preciosion+Recall} \tag{5}$$

Table 5 and Figure 6 compares the performance of two ML models: one predicts irrigation and the other predicts climate indicators; all these models are evaluated based on four primary classification metrics: Accuracy, Precision, Recall, and F1-Score. The blue and red bars indicate that the performance of the irrigation prediction model and that of the climate-indicator prediction model, respectively.

The irrigation model performs better across all metrics than the climate model, and the recall (92.4) and accuracy (91.3) are significantly better which means that this model offers strong capability to estimate when irrigation is required. Although the climate model is still doing fairly well, it has lower recall (85.1%) and precision (87.2%), which implies that it may sometimes fail to detect actual climate change indicators or show false positive results.

Table 5. Performance Comparison of Proposed Work

Metric	Irrigation Prediction	Climate Indicator Prediction
Accuracy	91.3	88.7
Precision	89.6	87.2
Recall	92.4	85.1
F1-Score	91.0	86.1

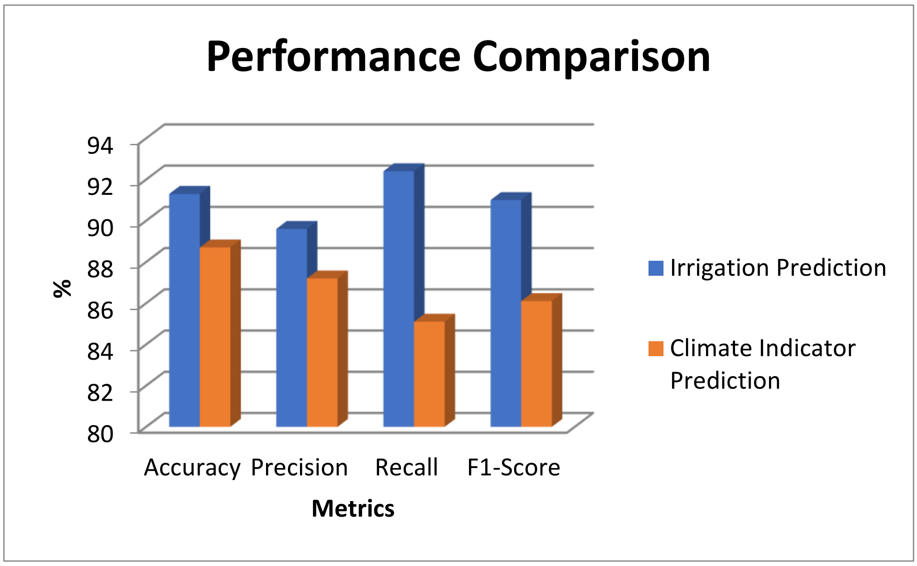

Figure 6. Performance Comparison of Proposed Work (Irrigation Prediction vs. Climate indicator Prediction).

Altogether, the performance of the irrigation case model is more stable and even, which is indicated in the higher F1-score (~91%), so it is a suitable case to be automatized in the real-time autonomous system of water management.

4.1 Irrigation Prediction

Irrigation prediction is a way of forecasting the most appropriate time to irrigate a crop and the volume of water needed by the plant through the surroundings and soil-related to the environment like soil moisture, temperature, humidity, rainfall, and sunlight and wind velocity. In automatic irrigation system, proper prediction of irrigation process is very critical in order to make sure that it delivers water at the right time and in the right conditions without interventions. Not only does this help in conserving water which is a major raw material in agriculture but it also makes the crops healthier because it guards against under and over irrigation. Such systems can potentially make real-time decisions, which are data-driven and dynamic with regards to changing weather and soil conditions by combining sensor data with machine learning or AI-based models. Advantageously, this leads to increased water use efficiency in irrigation forecasting, decreased energy and labour cost, as well as sustainable agriculture among others particularly in areas prone to water shortages and environmental fluctuation.

The performance of the proposed CNN model is compared with commonly used machine-learning algorithms like RF, SVM, and LR and the results are compared in Table 6 and Figure 7. The proposed CNN model achieved the best accuracy of 91.3% which outperforms the Random Forest, SVM and Logistic Regression with accuracy rates of 87.0%, 86.7% and 84.9% respectively. Likewise, the CNN model achieved the highest recall of (92.4%) and F1-score of (91.0%) as it was best able to correctly identify irrigation requirements and climate-related conditions.

There is a significant improvement in performance compared to LR, with a 6.4% increase in accuracy. The proposed model improved the results by 4.6% and 4.3% over SVM and Random Forest respectively. The results indicate that the CNN structure is better for learning the complex nonlinear relationships between soil moisture, soil temperature, soil humidity, rainfall and image features related to crops. The CNN autonomously generates features from multimodal agricultural data that are representative and hence improves prediction performance, compared to the conventional machine learning models that heavily depend on manually engineered features.

The improvement brought by the proposed model is meaningful for the intelligent irrigation management from the application point of view.

Table 6. Irrigation-Prediction Performance

Model	Accuracy	Precision	Recall	F1-Score
CNN (Proposed)	91.3	89.6	92.4	91
Random Forest [24]	87	87	86.8	87.2
SVM [25]	86.7	85.1	85.8	85.4
Logistic Regression [26]	84.9	82.7	85	83.9

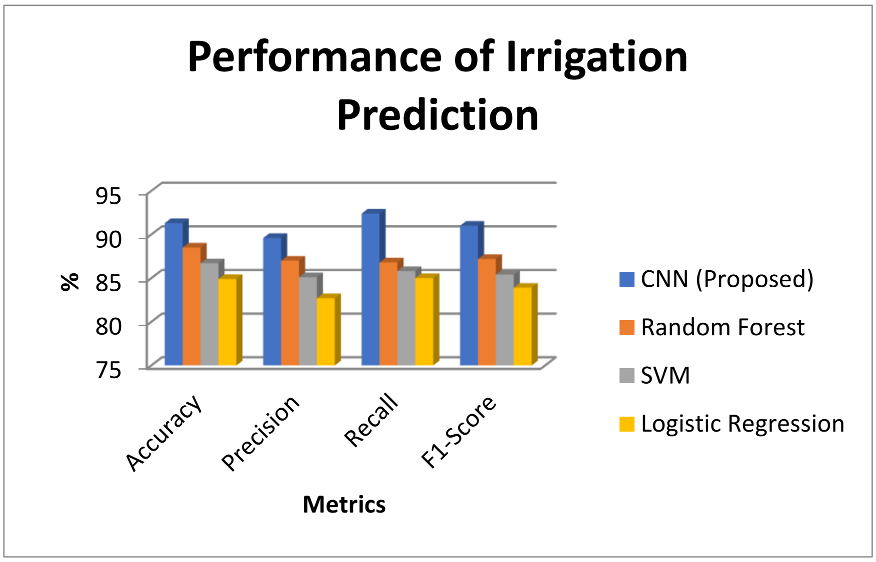

Figure 7. Performance Analysis of Irrigation Prediction.

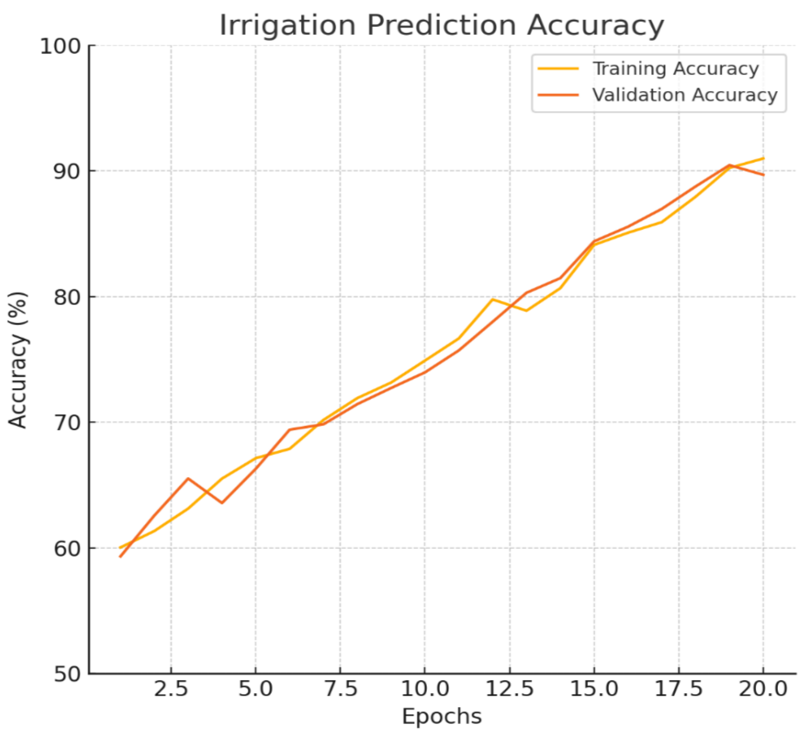

Figure 8. Accuracy of irrigation prediction in training vs. validation.

A rise in prediction accuracy of just 4-6% can make a significant difference in the reduced number of irrigation events that are unnecessary, increase irrigation water use efficiency and increase crop productivity. Thus, the achieved performance improvements are not only statistically significant, but also meaningful in the context of smart farming for climate.

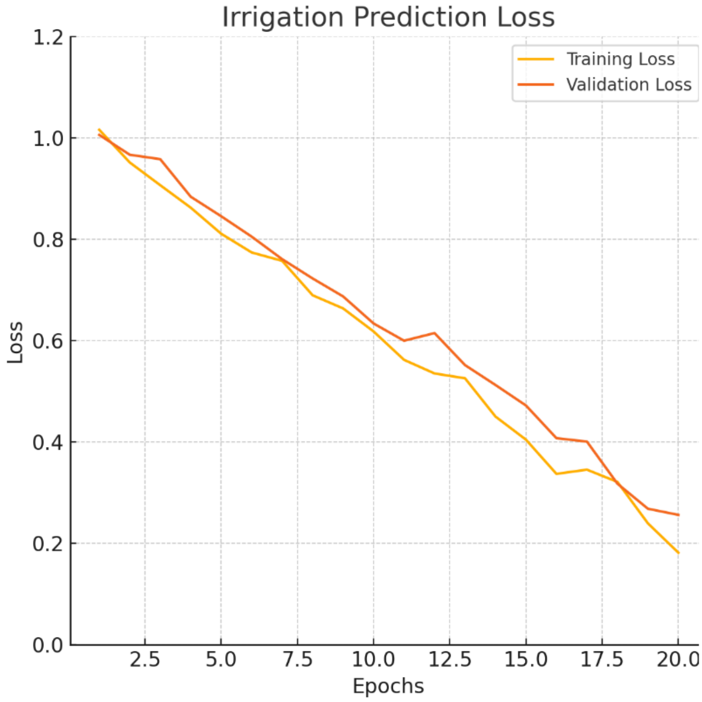

Figure 9. Loss Analysis of Irrigation prediction in Training vs. validation.

In addition, the results align with recent research in the field of AI-driven irrigation and precision agriculture, which has demonstrated the success of deep learning methods in dealing with mixed agriculture data. The strong 92.4% recall value is especially significant as it decreases the likelihood of missing irrigation requirements, so lowering the risk of water stress in crops. In general, the comparative study shows that the proposed CNN-based framework is an effective and reliable climate-aware irrigation decision support system.

Figure 8 shows the training as well as the validation accuracy as a function of 20 epochs. Both training accuracy (orange line) and validation accuracy (red-orange line) have a steadily increasing trend, so the model learned more effectively as it was trained further. The accuracies begin with about 60% and keep increasing to an approximate of 91% at the 20th epoch. This slight variation between the training and validation curve indicates that the model will probably make good predictions on the hidden data, and there is no indication of overfitting. The trend reinstates the strength and practicality of the training process toward the irrigation prediction task.

Figure 9 shows the loss graphs of training and validation throughout 20 epochs. The trend of both training loss and validation loss is also decreasing and their curve initially starts at 1.0 and then reduces to 0.2. The gradual reduction indicates that the model is learning from the training data and is improving over time. The training loss results and the validation ones are very close, indicating good generalization to unseen data and little evidence of overfitting. The low variance in the validation loss is expected and it is not a sign of instability. All in all the figure illustrates well behaved learning process of the irrigation prediction model.

4.2 Climate Indicator Prediction

Climate-indicator prediction is the forecast of climate indicators of the environment in the form of temperature anomalies, precipitation patterns, humidity or sunlight strength that indicate changes in the climate. When applied to the process of automatic irrigation, forecasting of such climate indicators is important as its results directly affect crop water demand and changes of the soil moisture relations. As an example, a potential heatwave, dry period, or rain might take much longer than anticipated and change the irrigation requirements greatly. When farmers combine climate indicator projection on irrigation control with watering timings so as to conserve available water, optimum water usage; crop stresses; and avoid futile water consumption during rains, despite water stress levels during non-rainy periods. This does not only result in an improvement in water use efficiency but also in the healthiness of crops, operational cost savings and helps in sustainable agricultural activities in the wake of rising climate variability.

Table 7 and Figure 10 compares the performance of four machine learning models, namely, the proposed CNN, RF, SVM, LR, in performing climate-indicator prediction by using sensor data. The metrics being used are accuracy, precision, recall and F1-score. As illustrated in the graph and table, the proposed CNN model performs better than the other models in all the metrics with the highest accuracy of approx. 88.7% as well as precision, recall, and F1-score of approx. 87.2%, 85.1%, and 86.1% respectively.

Table 7. Performance of Climate-indicator prediction

Model	Accuracy	Precision	Recall	F1-Score
CNN (Proposed)	88.7	87.2	85.1	86.1
Random Forest [24]	86.2	85	82.4	83.5
SVM [25]	84.1	83.5	80.2	81.7
Logistic Regression [26]	82.3	80.1	76.5	78.2

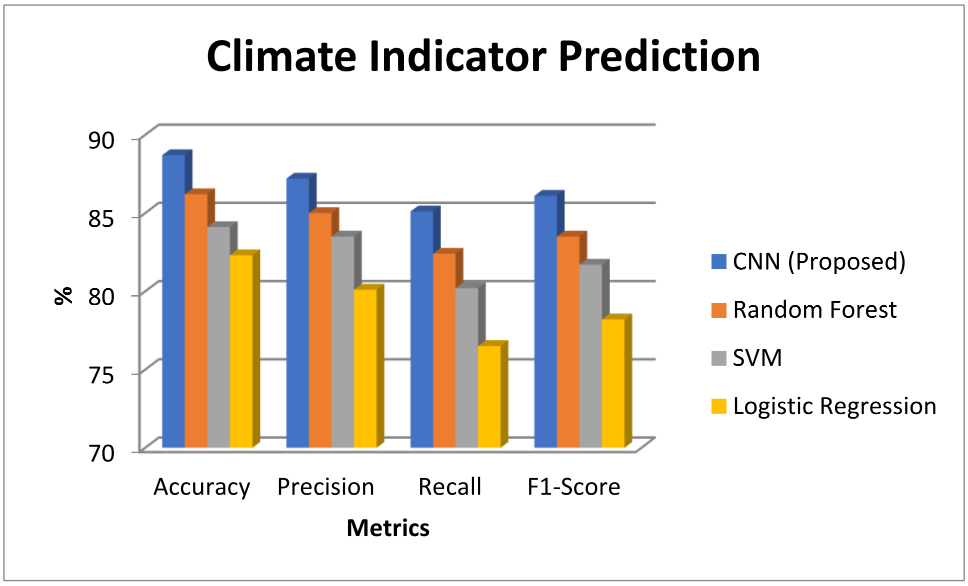

Figure 10. Performance Analysis of Climate-Indicator Prediction.

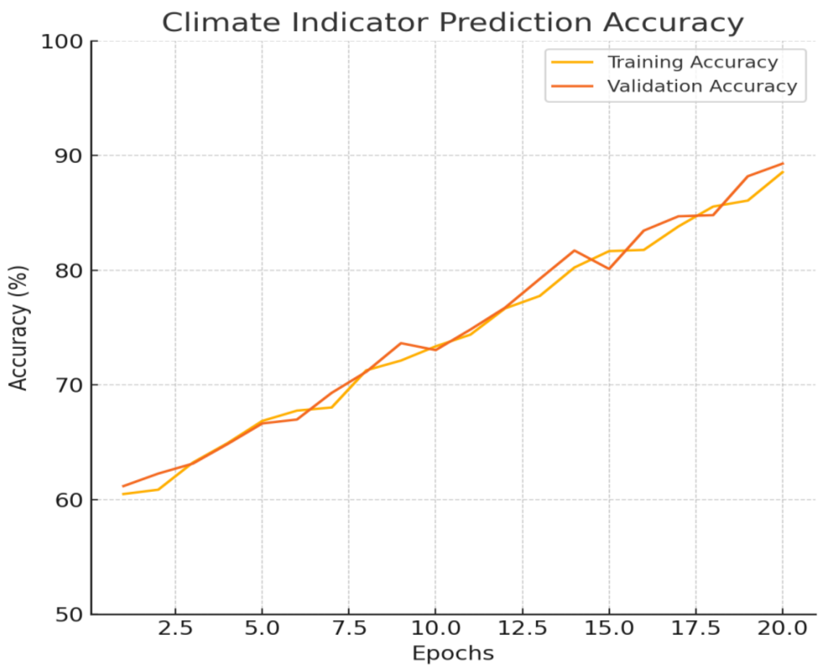

Figure 11. Accuracy Analysis of Climate Indicator Prediction in Training vs. validation.

SVM, LR and RF clinch in that order. There is a remarkable difference when comparing the performance of LR in every measured parameter; it performed the worst in both recall and F1-score, which means that it is not very good at spotting significant changes in climate indicators. This high performance of CNN is owed to the fact that they are capable of extracting and learning temporal, spatial patterns of multivariate sensor data that enhance such sensors to detect the minute changes in the environment that are related to climate monitoring processes.

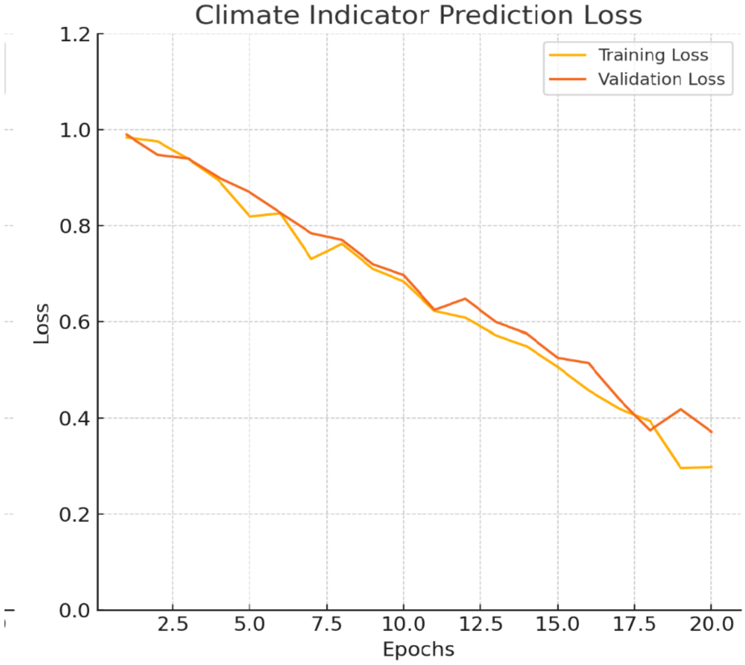

Figure 12. Loss Analysis of Irrigation Prediction in Training vs. validation.

Figure 11 demonstrates the way the model improved with each training epoch across 20 training epochs. The training and validation accuracy increased to approximately 91 % at the last epoch where the training and validation accuracy were approximately 60 % at the beginning. The validation training curve and the training curve follow each other closely during the training period which implies that the model is learning but not overfitting. Such great similarity is an indication of excellent generalization to unseen information. The growth towards the optimal performance is also a good sign that the training process is successful as both curves become stabilized towards the end of the irrigation prediction.

Figure 12 indicates the loss curve during training and validation over 20 training epochs. The loss of both curves starts with a high value of about 0.98 and gradually shrinks to about 0.3-0.4 at the last epoch. The training loss and validation loss follow the same pattern, and are going down, indicating progressive learning and a suitable model generalization. There is nothing unusual in low variations in the validation loss, which implies a slight inconsistency in the model because of the invisible data, yet the steady coherence to the training loss implies a potential with the model being not overfitted. This graph proves that the model is successfully reducing error with time, at the same time not oscillating a lot during training.

5. Conclusion

This study demonstrates that CNNs combined with sensor data, as a form of Machine Learning, is a powerful approach for both climate change indicators prediction and the aim of the automated irrigation. The CNN-based model provided better results compared to the conventional machine-learning models in essential performance indicators of accuracy, precision, recall, and F1-Score. In prediction of irrigation, an F1-score of 91.0% was recorded and this aspect ensures that sufficient and accurate delivery of water is attained within schedules, whereas 86.1% F1-score was obtained in climate-indicator prediction making it possible to capture fine-tuned change in environment. These findings affirm that CNNs have the ability to abstract complicated temporal and environmental rhythms out of sensor data streams such that it can support data-driven decision-making during real-time situations in precision agriculture. Not only does the system save water and energy, but also improves crop resilience and health due to climatic variation, which is a huge step towards intelligent and sustainable agriculture practices.

The originality of the proposed work does not lie in introducing an entirely new stand-alone learning algorithm, but rather in offering a new intelligent irrigation system that combines of CNN-based crop and environmental feature learning, multimodal sensor-data fusion, hierarchical irrigation control logic, and a solar-powered remote monitoring architecture into one single decision-support system. The proposed contribution is uniquely characterized by its multi-layer pipeline of inference visual crop analysis via CNN with real-time sensor measurements, threshold-based fail-safe irrigation activation, and statistical analysis of rainfall and moisture to generate adaptive irrigation control. In contrast to traditional smart irrigation systems where they mostly depend on pre-determined thresholds or remote sensor readings, the proposed system proposes image-based learning, environmental sensing, and automated control systems within a single deployable system and enabled by mobile monitoring. Thus, it is the multimodal data fusion and combined control architecture that is new, not the suggestion of an entirely new CNN algorithm. This stance has been explained in the updated manuscript and contrasted to recent smart irrigation literature by highlighting the intelligent integration of the system level, adaptive decision-making ability and practical deployment design.

Moreover, future work could involve further integrating multimodal AI models to analyze field images and sensor readings alongside satellite images and meteorological information to improve climate forecasting and irrigation scheduling. OpenAI's technology could be integrated into autonomous farm management systems, enabling precise forecasting of water needs, optimized irrigation, and improved resource management, which could help boost crop yields, conserve water, and promote sustainable farming. The integration of OpenAI's technology with autonomous farm management systems could lead to more efficient water use, predictive maintenance, and adaptive irrigation practices, contributing to better crop yields, water conservation, and sustainable farming.

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Authors Contribution Statement

S. Gomathi: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. D. Thaiyalnayaki: Methodology, Validation, Formal analysis, Investigation, Data curation. J. Santhosh: Software, Resources. K. Padmini: Conceptualization, Formal analysis, Visualization. S. Kannan Shanumgam: Project administration, Writing – review & editing, Supervision. All the authors have read and agreed to the published version of the manuscript.

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Competing Interests

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

AI Disclosure Statement

The authors used an AI-assisted tool (CANVA) solely for the generation of illustrative figures, flowcharts, and conceptual diagrams used to improve the visual presentation of the proposed framework. The AI-generated visual content was subsequently reviewed, modified, and validated by the authors to ensure technical accuracy and consistency with the research objectives. No AI tool was used for data analysis, model development, experimental evaluation, interpretation of results, or generation of scientific conclusions. The authors take full responsibility for all content presented in this manuscript.

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