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AI-Driven Deep Learning Water Resource Management System for Crops in Pakistan

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Agriculture is one of the pillars of the Pakistani economy and the utilization of water in the fields significantly impacts productivity and sustainability. However, water scarcity, irregular rainfall, the broader impact of climate change, and a reliance on the farmer's own decisions for irrigation remain challenges in the sector. To address these gaps, an Artificial Intelligence (AI) based Hybrid Convolutional Neural Network – Long Short-Term Memory (CNN-LSTM) framework is proposed that enables intelligent water resource management and crop irrigation forecasting in Pakistan. The proposed system combines two complementary datasets, one for Pakistan weather (41,125 records) and one for agricultural crop production (33,125 records) to form a combined corpus of 74,250 records that include temperature, rainfall, humidity, wind speed, atmospheric pressure, crop type, cultivated area, yield, and seasonal information. The full corpus was split into a training, validation and test set of 70, 15 and 15 respectively. The model training process was preceded by a standard preprocessing pipeline, which involved handling missing values, Min–Max normalization, label encoding of categorical features, preparing sequences using a sliding window, and light augmentation. CNN layers are used to capture the spatial relationships among agronomic features and meteorological features within the hybrid network, and LSTM layers are used to capture the temporal features in the hybrid network, such as seasonal irrigation cycles and rainfall trends. The hybrid model reached an overall accuracy of 96.8%, with Precision = 95.9%, Recall = 96.3%, and F1-score = 96.1%. The error scores were also low: RMSE = 0.021 and MAE = 0.017. The proposed model outperformed the SVM, Random Forest, standalone CNN and standalone LSTM baseline by 2.7% to 8.1% in terms of accuracy, the highest improvement being achieved against SVM and the lowest improvement being achieved against the best CNN-LSTM baseline. On the water-use side, the simulation results suggest a potential reduction of approximately 32% compared to traditional water use when simulated scheduling was performed based on water use predictions from the model. The framework can be useful for farmers, extension officers, and policymakers to make informed decisions on irrigation and contribute to the overall efforts of climate-smart and sustainable agriculture in Pakistan.

Keywords: Artificial Intelligence, Deep Learning, Hybrid CNN-LSTM, Water Resource Management, Precision Agriculture

Introduction:

Agriculture is one of the most significant sectors for Pakistan, as it plays a vital role in the country's economy, employment, and food production. The efficient utilization of water is a crucial factor in crop production. However, water management can reduce yield and farm expenses if not done properly [1]. This issue is more serious in countries such as Pakistan where agriculture consumes significant water resources [2]. Hence, water resource management is one of the key fields of study to enhance agricultural productivity and sustainability. Water resource management involves the planning, monitoring and utilization of water for the reduction of wastage and maintenance of crop growth in the long term [3]. In agriculture, this involves determining the best time to irrigate, the amount to use and how to adapt the irrigation to crop type, weather, soil and season [4]. Traditional irrigation methods are sometimes based on experience, not data. This can result in over-irrigation, under-irrigation and in the use of water that is not efficient. To this end, water management is shifting towards intelligence and data in modern agriculture.

This research falls under the subdomain of water resource management with the use of artificial intelligence in precision agriculture. In this region, AI, machine learning and deep learning models are applied to process agriculture and weather data [5]. These models can acquire the hidden patterns from temperature, rainfalls, humidity, wind speed, air pressure, crop types, cultivation areas, production, yield and seasonal variations. From these patterns, the system can make a prediction of crop water requirements and make informed irrigation decisions. The main focus of this study is to use a hybrid CNN-LSTM deep learning model for predicting the CWR in Pakistan [6]. The CNN part is used to detect significant spatial aspects from the crop and weather data. The LSTM component learns the time series patterns like seasonal variations, rainfall trends, and irrigation demand variations over time. The proposed system is designed to enhance the irrigation forecasting capabilities and help achieve sustainable water use in crop production by integrating the above two models [7].

Poor irrigation management, water scarcity and climate change are emerging as serious issues in agriculture. Previous research suggests that machine learning has significant promise in the field of water resources prediction, monitoring, and planning. The author described the various water management tasks that can be assisted by machine learning such as forecasting, optimization and water quality monitoring [8]. This encourages the adoption of intelligent models for agricultural water management rather than manual and traditional methods. [9] Has discussed the difficulties of water planning because of Climate change. Water resource management should be adapted to changing climate conditions, as discussed. This is significant for Pakistan as it can directly affect the productivity of crops due to irregular rainfall and increasing water stress if not planned properly. Water quality and monitoring issues are also a problem in Pakistan. [10] Discussed the water quality assessment and monitoring problems in Pakistan and emphasized the importance of adopting good management practices. The problems demonstrate that there is a need for intelligent systems in Pakistan which integrate the weather data with the crop data to assist in practical irrigation decisions. This encourages the development of an AI-based deep learning system to predict the water requirement of crops and minimize water loss. The landscape of agricultural water management has undergone a significant transformation in recent years, thanks to the development of various technologies such as Artificial Intelligence (AI), Internet of Things (IoT), precision agriculture, and climate-smart irrigation systems. Recent research has shown the effectiveness of AI-driven irrigation systems based on deep learning, remote sensing, and real-time environmental monitoring to enhance crop productivity and water use efficiency in a changing climate [11][12]. Moreover, intelligent irrigation systems have been found to have great potential in the field of sustainable agriculture in water scarce areas and developing countries when combined with machine learning techniques [13][14]. AI-powered water management systems can contribute to water efficiency and climate resilience in Pakistan, where water management is a major concern due to irregular rainfall, groundwater depletion, and inefficient water management practices [15][16]. Hence, the aim of this research is to create an intelligent Hybrid CNN-LSTM framework especially designed for the agricultural and climatic condition of Pakistan.

Climate change, erratic rainfall, groundwater depletion, inadequacy of irrigation infrastructure, and growing demand for water by crops are posing serious water management problems in agriculture in Pakistan. The traditional irrigation methods are mainly based on the estimation by hand and farmers' experience, which often leads to over-irrigation, under-irrigation, water wastage, and lower productivity. Most of the water resource management machine learning and deep learning solutions are developed for specific hydrological problems, including streamflow forecasting, groundwater prediction, water quality monitoring, etc., and very few efforts have been made to develop intelligent irrigation prediction systems for specific crops based on integrated agricultural and weather datasets in Pakistan. Moreover, many of the current models are not able to simultaneously reflect the spatial environmental relationship and the temporal irrigation dependency needed for accurate forecasting of crop water requirements. Hence, an intelligent and efficient AI-based framework is needed to integrate multidimensional agriculture and climate data to support sustainable irrigation management and climate-resilient agriculture in Pakistan.

Research Objectives:

The main aim of this research is to design an Artificial Intelligence (AI) based intelligent water resource management system with the help of a Hybrid CNN-LSTM model for sustainable crop irrigation prediction in Pakistan. Specific Objectives are as follows:

RO1: To procure and preprocess agricultural crop production and hydro-meteorological data for prediction of crop water requirement in Pakistan.

RO2: To design a Hybrid CNN-LSTM deep learning model that can learn spatial environment information and temporal irrigation process from multi-dimensional agricultural data.

RO3: To study the effect of climatic and agricultural parameters such as rainfall, humidity, temperature, type of crops, area of cultivation and seasonal changes on prediction of irrigation.

RO4: To evaluate the predictive performance of the proposed Hybrid CNN-LSTM framework against the conventional machine learning and standalone deep learning models such as SVM, Random Forest, CNN and LSTM.

RO5: Assess the effectiveness of the proposed framework based on the standard evaluation metrics, such as Accuracy, Precision, Recall, F1-score, RMSE and MAE for sustainable water resource management.

Research Novelty:

Many recent works have investigated CNN-LSTM models for water-related forecasting, but they have considered various problems, such as groundwater level forecasting [9], water quality forecasting [10] and hydrological simulation in Nepal [11]. The novelty of the present work is threefold, and lies in the three concrete technical choices, which are made together and which distinguish the present work from the prior art. First, to the best of our knowledge, few studies have investigated CNN-LSTM-based crop irrigation forecasting using integrated crop and weather datasets in Pakistan which combines two separate datasets from Pakistan (weather dataset of 41,125 records, crop production dataset of 33,125 records) into one feature space. The climatic data and the hydrological data (gauge data) are used separately in previous CNN-LSTM water studies, without incorporating the crop type, cultivated area, yield and seasonal cropping calendar as direct inputs along with the meteorological data. Second, the spatial branch of the network has been designed to recognize the multi-variable input as a feature map, instead of a flat vector, so that the convolutional filters can detect cross-feature interactions (e.g., the combination of low humidity and high water demand crop like rice) which cannot be easily captured by a flat model. The temporal branch is then applied to the sliding-window sequence of these learned representations, and The LSTM processes the fused weather-crop features instead of raw signals. Thirdly, the evaluation is based on a Pakistan-relevant downstream outcome (estimated irrigation water savings) along with the standard classification metrics. This contribution level framing is not widely used in previous CNN-LSTM water studies, where most of the studies end at error metrics. These choices provide a regional context and more end-use motivation than the current CNN-LSTM literature.

Research contribution:

This research introduces an AI-based hybrid CNN-LSTM model to estimate the water demand of crops and assist water resources management in Pakistan. The framework incorporates weather and crop production data and learns relationships between the two and irrigation requirements. The contribution is significant as the water management in Pakistan still relies on the traditional practices and the personal judgment of the people. The second contribution is the use of preprocessing and sequence preparation techniques to enhance data quality prior to model training. The data is prepared for deep learning using techniques like missing value handling, normalization, feature scaling, categorical encoding, and sequence generation. The proposed model is able to learn more stable and meaningful patterns from multidimensional agricultural data via the following steps. The third contribution is the performance comparison of the proposed hybrid model with the conventional machine learning model and standalone deep learning model. The proposed Hybrid CNN-LSTM model showed the accuracy of 96.8%, RMSE of 0.021, and MAE of 0.017, as reported in the paper. This indicates that the use of CNN and LSTM for irrigation prediction for crop water management has better performance than using only CNN or LSTM.

Research Gaps:

While several research studies have applied machine learning and deep learning in water resource management, most studies have been limited to solving individual water-related problems. Some of the studies are on groundwater prediction; some on streamflow forecasting; and others on water quality assessment. Predicting streamflow with deep learning and machine learning models was the focus of [12]and predicting drinking water shortage by deep learning was explored by [7]. All these studies are helpful but are not directly helpful in solving the problem of crop irrigation prediction in Pakistan. Another limitation is the lack of integration of crop production data and weather data for irrigation decision support for many of the existing approaches. Crop water requirements are determined by both agricultural and environmental conditions. Models that rely solely on weather data, or solely on hydrological data, may not capture important crop-specific patterns. This results in the need for an integrated model that can handle crop type, area of cultivation, yield, and rainfall, temperature, humidity, and seasonality. Another gap is that there is no AI systems specifically designed for agricultural water resource management in Pakistan. The conditions of Pakistan are different, irrigation is different, crop pattern is different, and water management problems are different. Hence, the models developed elsewhere might not be applicable in the context of Pakistan. To fill this gap, this research introduces a hybrid CNN-LSTM model for predicting the water requirements of crops, based on crop and weather data from Pakistan.

Literature Review:

The body of literature on water resource management with the aid of Artificial Intelligence has been rapidly expanding in the last five years. This section does not summarize each study individually, but rather categorises the studies according to the problem area, summarises the strengths of each group of studies and points out the weaknesses that the current study seeks to overcome.

Machine Learning for Hydrological Forecasting:

[17] Examined the integration of machine learning and hydrological simulation and found that the integration of the two models can be used to enhance the accuracy and decision support of the model. [18] Studied time-series prediction at unmonitored sites and demonstrated that machine learning is able to deal with missing data. The overall value of intelligent and digital tools for water planning was confirmed by [19] and [20]. The advantage of this collection of work is its generality, that is, the methods are applicable in many hydrological situations. The drawback of these reviews is that they are systems-level reviews and do not create a model that a farmer or extension officer in Pakistan can act upon, relevant to the present study. They also seldom include crop-side variables.

Streamflow, Groundwater and Water Quality Prediction:

[21] Used deep learning and machine learning for streamflow forecasting for sustainable water supply and concluded that deep models are better than classical regression. Using deep learning, [22] predicted drinking-water shortages under climate change. In watersheds where streamflow data are aggregated and intermittent, [23] suggested a deep learning method for streamflow prediction. In Taiwan, the largest alluvial fan, [24] has developed a hybrid deep learning model for groundwater level forecasting. A hybrid deep learning model for water quality prediction was proposed by [25]. A common shortcoming of all these studies is that they consider water as a hydrological resource only and do not consider the crop-level demand. The proposed work is different in that it uses crop water requirement as the primary forecasting target, instead of streamflow, groundwater level or water quality.

Hybrid CNN-LSTM Architectures:

A hybrid CNN-LSTM network was used by [26] to simulate hydrology in Nepal and achieved good results in capturing complex hydrological patterns. A similar hybrid was used for water quality by [10]and for groundwater by [27] using deep learning. The above studies validate the proposed combination of convolutional layers with recurrent layers when the data is spatially structured and temporally dependent. This paper directly addresses the gap that none of these CNN-LSTM studies have been applied to crop-level irrigation forecasting in a country-specific agricultural context and none of them combine weather and crop production data as described in this paper.

Climate Change and Water Management:

[28] Explored how water resources management would change under climate change and suggested the need for adaptive and intelligent systems. Using machine learning, [29] analyzed the effects of climate change on groundwater. In the work [30] precipitation reanalysis products were statistically and machine learning evaluated by nature-inspired optimization. The common theme is that water management strategies must now be prepared to deal with non-stationary conditions. None of these studies, however, make this argument deployable as a crop irrigation tool in Pakistan, as this work tries to do.

Water Management in Pakistan:

A review of water quality assessment and monitoring in Pakistan was carried out by [31] which revealed that water contamination, poor monitoring and weak institutional response were recurring problems. The gaps were highlighted by [32] in the context of drinking water management in Pakistan. The drinking water quality in the southern part of Sindh was reported by [33]. These contributions clearly show the local water situation, but are directed at drinking water and surface water quality, not at agricultural water demand. The proposed model thus fills the gap of the literature by focusing on the irrigation side of Pakistan's water problem.

Recent AI-Driven Precision Agriculture and Smart Irrigation Studies:

In the past five years, there have been several works that have focused on irrigation and precision agriculture using AI. In precision irrigation, [34] surveyed the use of deep learning models and found that hybrid temporal-spatial models have a better performance than classical regression. For arid areas, [5] suggested an LSTM-based irrigation scheduling model and showed that it can save about 25% of water compared to fixed schedules. [21] Used transfer learning to estimate crop water stress, but observed a decrease in performance in areas where local fine-tuning data were not available, which is the motivation behind the use of a dataset specific to Pakistan here. In [35] they studied IoT enabled smart irrigation pipelines and emphasized that the AI model is not always the limiting factor, but rather the availability of data and sensor reliability. In line with the current study, [22] examined the concept of climate-smart agriculture in South Asia and explicitly requested country-specific AI models.

Summary of the Identified Gap:

The previous research shows that the hybrid deep learning models are appropriate for water-related forecasting and that the adaptation and climate-responsiveness of forecasting models is becoming more critical [36]. What is missing is a CNN-LSTM model trained on Pakistani weather and crop data, which integrates agronomic and meteorological variables in the same model, and which is evaluated on not only the standard error measures, but on an irrigation outcome in the downstream. The proposed framework is intended to address this need.

Methodology:

Research Design:

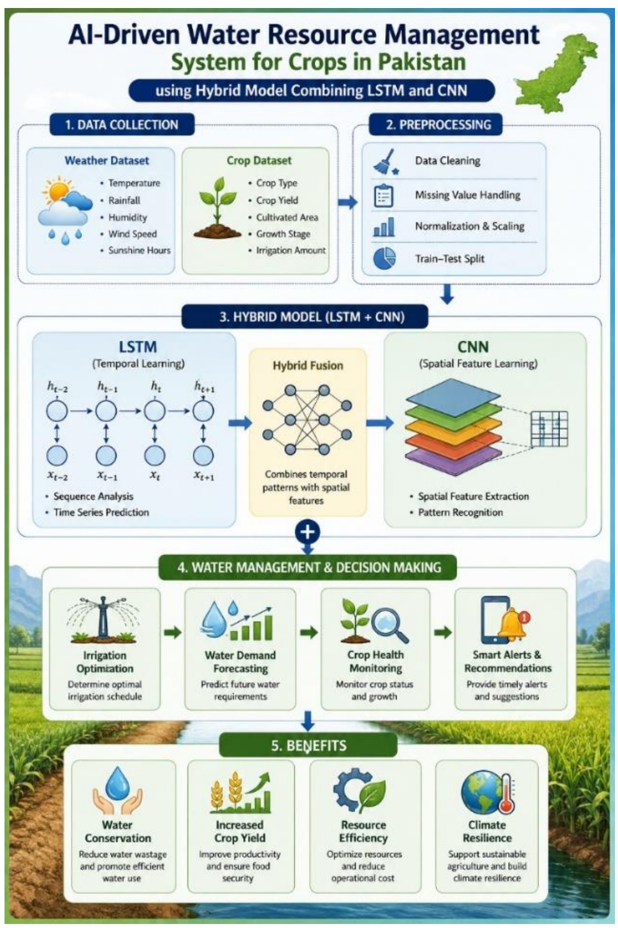

Figure 1. Research Design

For this research, it is a quantitative and experimental research design that is used to come up with an AI-based deep learning Water Resource Management system for crops in Pakistan, using a hybrid CNN-LSTM model. The study is a combination of weather and agricultural crop production data to examine the relationship between climatic conditions and crop water requirements. Next, data preprocessing techniques such as data cleaning, normalization, feature scaling, handling of missing values and sequence generation are implemented to enhance the quality of data and the performance of the model. Processed data sets are subsequently split into a training set and a testing set, with the aim of developing the model and evaluating it. The proposed architecture uses the Convolutional Neural Network (CNN) to learn spatial and hidden patterns from the crop and weather data, and the Long Short-Term Memory (LSTM) network to learn temporal dependencies and sequential patterns related to the irrigation and environmental conditions. The proposed hybrid CNN-LSTM model is trained to forecast the CWR and optimal irrigation management for sustainable agriculture. The performance of a model is evaluated using accuracy, loss, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and prediction efficiency. The research design aims to improve water utilization, irrigation efficiency and productivity of crop under changing climate in Pakistan.

Dataset Description:

The proposed research was based on two integrated datasets, one of agricultural crop production data and second weather data from various areas of Pakistan. The crop dataset included important agricultural parameters such as crop type, cultivated area, crop yield, records of seasonal information and records related to irrigation, while the weather dataset included environmental parameters like temperature, rainfall, humidity, wind speed, etc., and atmospheric pressure. These datasets were chosen due to the strong dependence of crop water requirement to agricultural and climatic conditions, and irrigation management. The datasets were obtained from the public sources of agricultural and meteorological data such as government agricultural reports, climate monitoring data and online environmental repositories related to Pakistan. Data were collected over several cropping seasons and climatic variations, and were diversified and representative of the environment to predict irrigation needs. The proposed framework was able to learn different irrigation patterns across various agricultural regions and seasons. The data was preprocessed by ensuring its authenticity and reliability by selecting only verified and consistent data. Samples were removed to improve data quality and prediction bias due to being incomplete, duplicated, and inconsistent. In addition, before the model training, normalization, feature scaling, missing value filling and sequence preparation methods were used to enhance the efficiency and stability of the model. The need to balance the datasets to prevent bias of the model for certain irrigation conditions or crop categories was also taken into account. The dataset samples were analyzed, and a balance was achieved between the different irrigation requirement classes (low, medium, and high irrigation demand conditions). To address the issue of class representation and to boost the generalization ability of the Hybrid CNN-LSTM model, data augmentation and temporal sequence generation methods were also used. The reason for choosing these particular datasets was their direct relevance to the water resource management of agriculture in Pakistan. Crop production behavior and climatic fluctuations were also important drivers of irrigation demand, and the incorporation of the crop and weather datasets in the proposed framework was able to incorporate spatial environmental patterns and temporal long-term dependencies. This hybrid data structure proved to be very effective in predicting irrigation, water demand forecasting and adaptability to changing agricultural and climatic conditions.

The first dataset is the Pakistan Weather Dataset (PWD) which holds data regarding the historical climate from various locations of Pakistan. Meteorological parameters including temperature, precipitation, soil moisture, wind speed, atmospheric pressure and weather conditions are measured in the time series. The environmental parameters are very important in the studies of crop water requirements and irrigation planning in agricultural system. The weather data is used in this research to find climatic trends that impact water availability and crop growth. The data is preprocessed with methods like data cleaning, data normalization, missing value imputation, and sequence generation before it is used for model training. Sequential weather features derived from the processed weather are then fed into the hybrid CNN-LSTM model to learn the spatial and temporal correlations among the weather. The incorporation of weather information allows the proposed system to undertake intelligent prediction of the irrigation need value and make more sustainable water resource management possible for crops in Pakistan.

Table 1. Pakistan Weather Dataset Distribution

Class Name	Total # of records
Temperature Data	6,000
Rainfall Data	5,250
Humidity Data	5,625
Wind Speed Data	4,500
Atmospheric Pressure	4,000
Cloud Cover Data	3,500
Visibility Data	3,000
Dew Point Data	2,500
Weather Condition	3,000
Seasonal Weather	3,750
Total	**41,125**

Table 2. Agricultural Crops Production Dataset Distribution

Class Name	Total # of records
Wheat Crop	4,375
Rice Crop	4,000
Sugarcane Crop	3,500
Cotton Crop	3,250
Maize Crop	3,000
Barley Crop	2,250
Millet Crop	2,000
Oilseed Crop	1,875
Pulses Crop	2,125
Seasonal Crop Data	2,250
Yield Production	2,500
Cultivated Area	2,000
Total	**33,125**

https://www.kaggle.com/datasets/ahmddbilall/pakistan-weather

The second dataset employed in this study is Agricultural Crop Production Dataset that includes the information of agricultural production related to various kinds of agriculture and crops. Crop related features are included in the dataset such as crop type, cultivated area, production volume, crop yield information, seasonal changes, farming trends etc. These attributes can give useful information about the behavior of the crop and water consumption under various environmental conditions. This work aims to create an AI-based system for water resource management based on the crop dataset and the weather data through a hybrid CNN-LSTM model. The crop related parameters help the model to learn agricultural patterns and to better estimate crop water needs. The data is then preprocessed using techniques like feature scaling, categorical encoding, and sequence preparation, which enhance the model's performance. The integration of crop and weather data helps in making intelligent irrigation decisions, optimizing water use, and sustainable agricultural decision-making in Pakistan.
https://www.kaggle.com/datasets/usamadar370/agricultural-crop-production-data

Data Preprocessing and Augmentation:

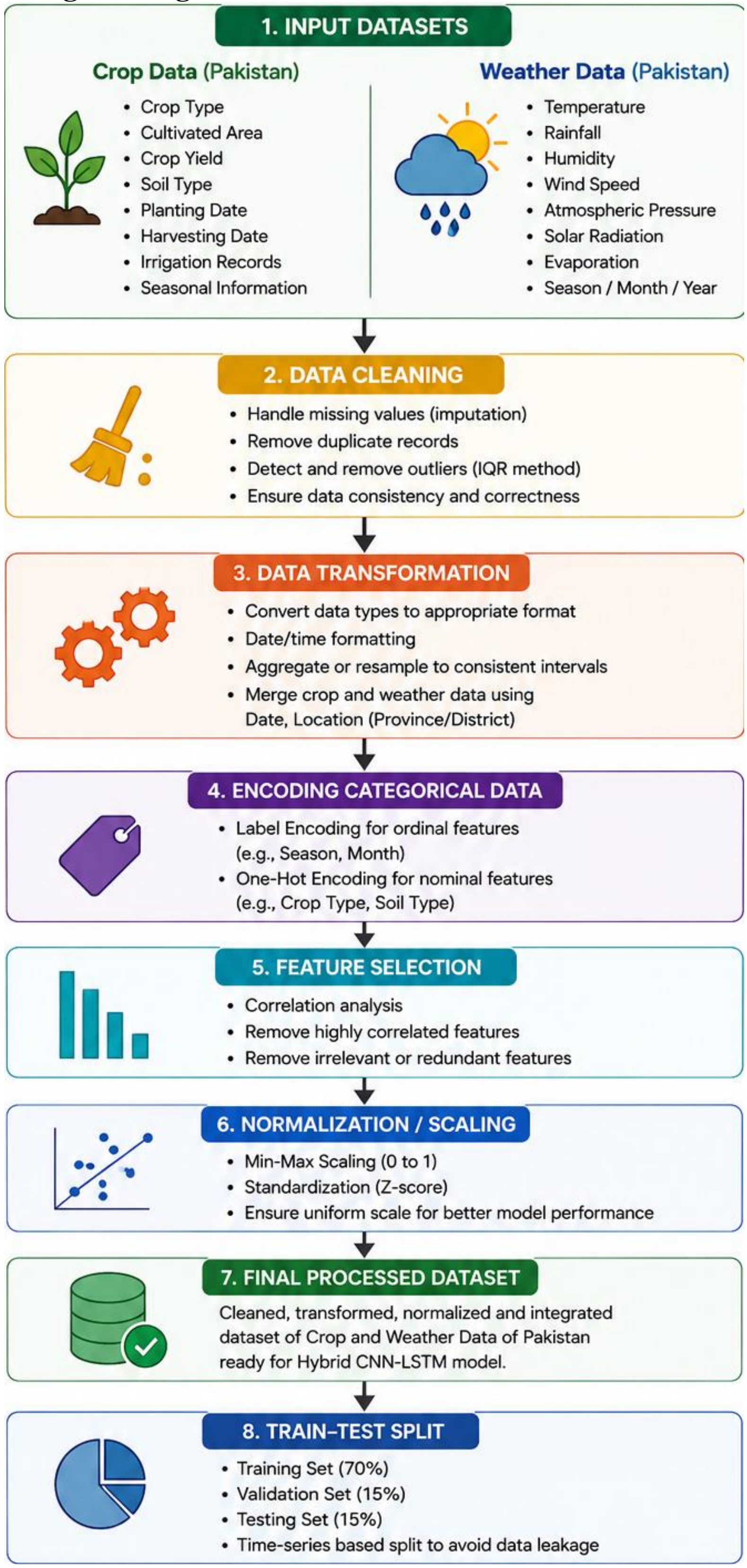

Figure 2. Preprocessing stages

The datasets of agricultural crop production and weather were collected and then preprocessed and augmented to improve the quality of the collected data, reduce noise, and enhance the performance of the model during training with the proposed Hybrid CNN-LSTM model. First, the missing and inconsistent values were detected and taken care of by using mean and Interpolation methods to keep the data consistent. To optimize computation and data reliability, duplicate records and irrelevant attributes were removed. Temperature, Rainfall, Humidity, Atmospheric pressure, Wind speed, Crop area, Yield obtained from the numerical features were normalized by using Min-Max normalization, which maps all the values to a common range of 0 to 1. This normalization process led to a more stable training process and quicker convergence of the models. Label encoding methods were used for categorical variables like crop type and seasonal information to convert them into numerical values. To increase the generalization ability of the proposed framework, data augmentation methods were utilized to create a variety of training patterns from the agricultural data, which is limited. Multiple sequential samples for varying climatic and irrigation conditions were developed using temporal sequence augmentation and sliding window. Moreover, the introduction of random noise and shuffling of the data were used to mitigate the risk of overfitting and the robustness of the model in different environmental conditions. The entire data set was split into training, validation and test sets in a ratio of 70:15:15. The preprocessing and augmentation techniques helped to better represent the features, mitigate the model bias, and boost the overall predictive accuracy of the proposed Hybrid CNN-LSTM irrigation prediction system.

The complete dataset was divided into training, validation, and testing subsets using a standard 70:15:15 ratio. The preprocessing and augmentation procedures significantly improved feature representation quality, reduced model bias, and enhanced the overall predictive performance of the proposed Hybrid CNN-LSTM irrigation prediction system. Preprocessing stages have been presented in figure 2.

Hybrid CNN-LSTM Model:

The suggested work is based on Hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) deep learning framework to design a smart water resource management system for crops in Pakistan. The hybrid approach is tailored for handling complex agricultural and meteorological data, leveraging the capabilities of two types of networks: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This holistic deep learning approach allows the system to capture spatial and temporal crop and weather features well, enhancing the prediction accuracy and irrigation decision-making. The model proposed is designed to assist sustainable agriculture by forecasting the water requirements of a crop and to optimise the use of water for different climatic conditions.

The CNN part of the hybrid structure is tasked with discovering important spatial features, and identifying hidden patterns in the input data sets. The layers of CNN are fed with the input features of weather-related attributes (Temperature, Humidity, Rainfall, Atmospheric pressure, Wind speed, Seasonal conditions), and crop production attributes. The convolutional layers are used to extract meaningful representations of the data relevant to the crop growth and water use characteristics from the input data using multiple filters. To enable the model to learn complex relationships in the data, activation functions like Rectified Linear Unit (ReLU) are added to the network. After convolution, pooling layers are added to decrease dimensionality, computational complexity and keep the most important features extracted from the convolution process.

After feature extraction, the output feature maps are passed to the LSTM unit, which is dedicated for learning sequential and time series task. Many agricultural and weather related data sets are temporally dependent: that is, they are influenced by the data from the past. These are long-range dependencies which are well captured by the memory cell structure and the gating properties of the LSTM network, such as the forget, input and output gates. These gates control the information flow in the network, allowing the model to hold on to significant historical data, while discarding irrelevant information. This enables the LSTM network to get very close to learning the seasonality of irrigation, climatic changes and crop water demand trends over time.

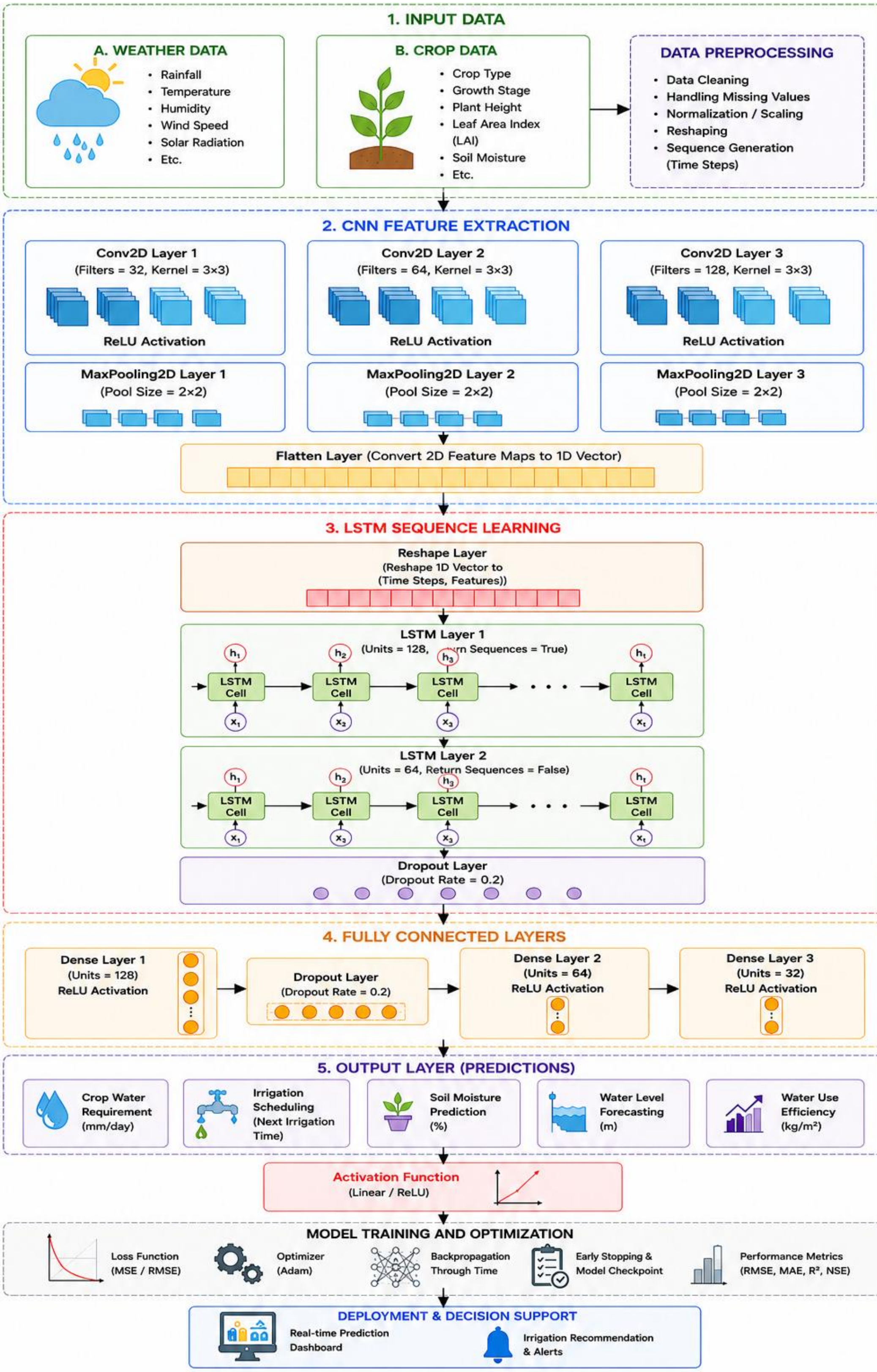

Figure 3. Detailed Hybrid CNN-LSTM Architecture Used in the Proposed Model.

By integrating CNN and LSTM networks with their respective feature extraction and sequence modeling capabilities, the overall learning ability of the proposed system is improved. The hybrid CNN-LSTM is trained with the historical data of the crops and weather after pre-processing (data cleansing, data normalization, feature scaling, and sequence preparation). In the training stage, the optimization strategies such as Adam optimizer and backpropagation algorithm are used to reduce prediction error and enhance the model's convergence. Model performance is assessed with the traditional performance metrics, including accuracy, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and loss values, to guarantee the reliability and effectiveness of modeling.

The proposed hybrid CNN-LSTM framework has many merits over the traditional machine learning and statistical approaches. The model has better prediction accuracy, generalization ability, good adaptability to nonlinear relationships and adaptability to the changes of environmental conditions. Besides, the model can process the spatial and temporal information simultaneously, which can be applied to handle the irrigation management and water resource planning intelligently and sustainably. Hence, the suggested CNN-LSTM based system can significantly contribute in the reduction of water wastage, better irrigation efficiency, increased crop productivity and support the climate resilient agriculture in Pakistan. In the figure 3, Hybrid CNN-LSTM Model have been presented.

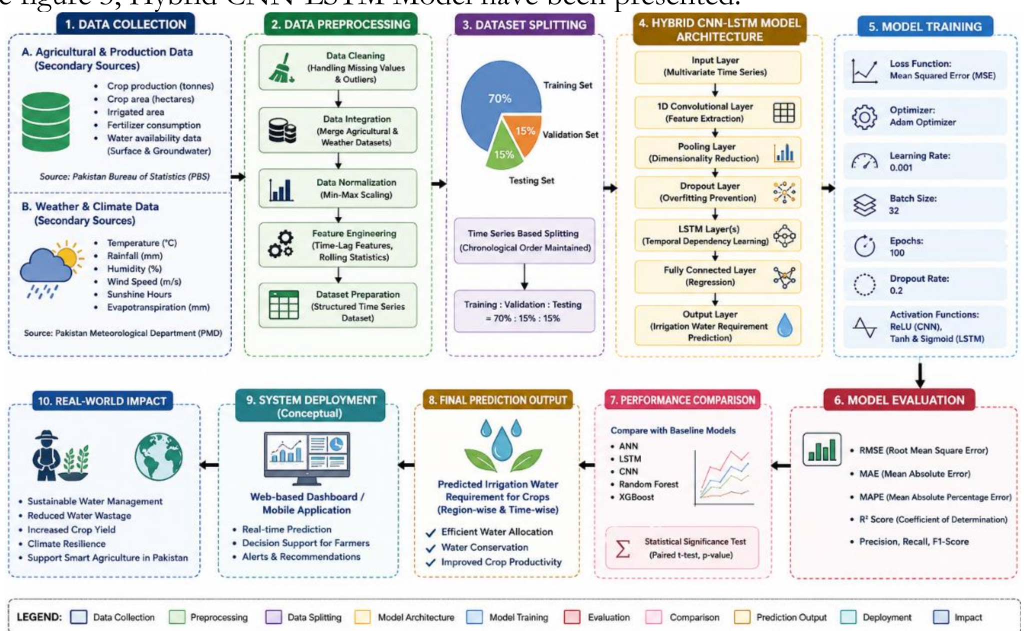

Figure 4. Overall Work flow of the Proposed Model.

Mathematical Formulation:

The proposed framework formalizes below the core operations for clarity and reproducibility.

The CNN block performs convolution operation:

$$y_{i,j} = f\left(\Sigma_m \Sigma_n x_{i+m,j+n} \cdot w_{m,n} + b \right) \qquad (1)$$

Let x denote the input feature map, w be the convolutional kernel of size m × n, b be the bias term and y be the output feature map, where $f(\cdot)$ is the ReLU activation function defined as $f(z) = \max(0, z)$.

The LSTM cell update equations are:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \qquad (2)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \qquad (3)$$

$$\tilde{A}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \qquad (4)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{A}_t \qquad (5)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t \odot \tanh(C_t) \quad (7)$$

The forget gate f_t, input gate i_t, and output gate o_t are all gates at time step t, C_t is the cell state, $\tilde{A}_t$ is the candidate cell state, h_t is the hidden state, σ is the sigmoid activation function, $\odot$ is element-wise multiplication, and W and b are learned weight matrices and bias vectors.

Loss function used when training: Mean Squared Error (MSE)

$$L_{MSE} = \left(\frac{1}{N}\right) \cdot \Sigma_{k=1..N}(y_k - \hat{y}_k)^2 \quad (8)$$

The Root Mean Square Error (RMSE) is used to evaluate the results.

$$RMSE = \sqrt{\left(\frac{1}{N}\right) \cdot \Sigma_{k=1..N}(y_k - \hat{y}_k)^2} \quad (9)$$

The evaluation method used is Mean Absolute Error (MAE):

$$MAE = \left(\frac{1}{N}\right) \cdot \Sigma_{k=1..N}|y_k - \hat{y}_k| \quad (10)$$

N is the number of samples, y_k is the actual value of the crop water requirement, and $\hat{y}_k$ is the value predicted by the model in equations (8)–(10).

Hyperparameter Configuration:

The hyperparameters of the hybrid CNN-LSTM model are presented in Table 3. The values are the ones used to create the architecture and training curves presented in Figures 3 and 5. They were selected empirically by observing the validation loss in a number of preliminary runs.

Table 3. Hyperparameter Configuration of the Proposed Hybrid CNN-LSTM Model:

Hyperparameter	Value
Optimizer	Adam
Learning rate	0.001
Batch size	32
Number of epochs	20
Loss function	Mean Squared Error
Pooling	MaxPooling with a pool size of 2×2.
Dropout rate	0.2
Activation Function	ReLU
Train / Validation / Test split	70 / 15 / 15

Experimental:

Model Training and Evaluation:

The preprocessed crop data and weather data is used to train the proposed Hybrid CNN-LSTM model to predict the CWR and generate better irrigation management. The data collected is then divided into training and testing sets in a suitable ratio to allow the model to be learned and thus to provide a fair test of the model. The complicated spatial and temporal relationships between the environmental factors and the agricultural parameters are obtained by using the training data set, while the testing data set is used to test the prediction ability of the model. The data pre-processing is a very critical process to ensure stability of the model and enhance the learning efficiency prior to the training of it. Methods can be normalization, feature scaling, sequence generation, handling missing values etc. During the training stage, CNN layers extract relevant spatial features from the crop and weather data, while the LSTM network learns temporal information of the data and the irrigation procedure over time. The parameters of the model are optimized using Adam optimizer, back propagation to minimize the prediction error, the convergence performance. Multiple epochs and multiple batch sizes will yield better accuracy of learning and reduce the risk of overfitting for training. The performance of the proposed model is evaluated using standard evaluation metrics like Accuracy, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Precision, Recall and Loss.

Experimental Setup and Tools:

Python-based tools and libraries were used to implement the Hybrid CNN-LSTM model in a simulated environment as presented in Table 4.

Table 4. Experimental Environment: Hardware and Software Specifications

Component	Details
Hardware Details	Device Name: DESKTOP-QI6H2EA Processor: Intel Core i5-6300U, 2.40–2.50 GHz RAM: 8 GB (7.88 GB usable) Storage: 466 GB HDD, 119 GB SSD Graphics Card: Intel HD Graphics 520, 128 MB System Type: 64-bit OS, x64-based processor
Software Details	Programming Language: Python Frameworks & Libraries: Tensor Flow, Keras, Numpy, Pandas, Scikit-learn, Matplotlib and Seaborn Cloud Platform: Google Cloud Platform(GCP) Compute Engine, Cloud Storage Operating System: Linux (Ubuntu)

The desktop system used for the experiments included DESKTOP-QI6H2EA, which had an Intel Core i5-6300U processor, 8 GB of RAM, 466 GB of HDD, 119 GB of SSD, and Intel HD Graphics 520. The software environment for Linux (Ubuntu) comprised Python with Tensor Flow Federated, Keras, Numpy, Pandas, and Scikit-learn. Furthermore, Cloud and Compute Engine services helped to complete computationally intensive tasks on the Google Cloud Platform, making it much easier to train and assess Hybrid CNN-LSTM model on the Crops and weather dataset.

Model Interpretability:

The proposed Hybrid CNN-LSTM framework includes interpretability as an important component as it helps to explain the deep learning model's predictions for crop water requirements and irrigation management. The decision-making processes of AI models are crucial in the context of agricultural and water resource management systems, ensuring reliability, transparency, and applicability. The proposed model will use spatial and temporal characteristics of the datasets to understand the relationship between weather conditions, crop production factors and water use patterns. The Convolutional Neural Network (CNN) block is used to detect relevant spatial features and relationships in agricultural and meteorological data in the hybrid architecture. The convolutional filters automatically learn important features such as rainfall pattern, temperature changes, humidity changes and the agriculture production behavior directly influencing the irrigation needs. The features extracted are fed into the Long Short-Term Memory (LSTM) network, which is able to model long-term temporal dependencies and sequential changes of the environment over time. The LSTM model's memory cells and gating mechanisms enable it to retain important historical data and forget the irrelevant data, which leads to more stable predictions and interpretation. Different visualization methods are used in feature importance analysis and prediction to understand how each input feature contributes to the prediction. The parameters such as rainfall, temperature, humidity, crop type, and seasonal variation are analysed to find out the impacts on water demand prediction. Moreover, training and validation curves, prediction graph and error analysis is employed to evaluate learning behavior and reliability of the model. The proposed Hybrid CNN-LSTM model introduces explainability, enhancing users' trust, transparency of water resources management and integration of AI systems in Pakistan's agriculture. The model offers insights into sustainable agriculture, water and climate resilience, and understanding of the relationships between the features and their predictions.

Model Evaluation:

Evaluation of the proposed Hybrid CNN-LSTM framework is an integral part of it and can assess the reliability, prediction accuracy, and overall effectiveness of the model in CWRM. The evaluation of the system is performed by the training and testing sets after the model training and interpretability analysis to test the system for its capacity to predict CWR under different environmental conditions. The preprocessed crop and weather datasets are split into two separated datasets to avoid bias while assessing the model and to get the right performance analysis. The complete analysis of the performance of the models is done with the help of some widely used evaluation criteria. The overall correctness of the predictions is measured by accuracy, the irrigation prediction and classification performance by precision, recall and the F1-Score. Furthermore, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to measure the error of prediction and reliability of prediction. The training and validation loss curves are also monitored to explore the model convergence, learning stability and overfitting phenomenon to ensure effective and sustainable prediction performance in agricultural water management systems. Evaluation parameters are presented in figure 5.

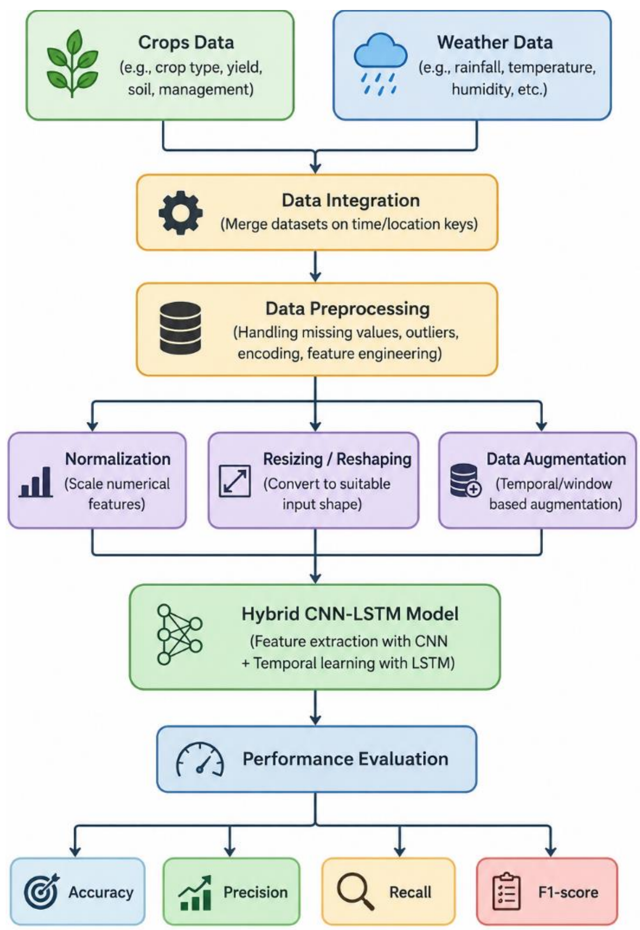

Figure 5. Performance Evaluation

Results and Discussion:

Hybrid CNN-LSTM deep learning framework has been tried to investigate its performance in Water Resource Management System (WRMS) and prediction of crop irrigation for Pakistan. Integrated agriculture crop production datasets and weather datasets (which include a variety of weather related and agriculture related parameters such as temperature, rainfall, humidity, wind speed, atmospheric pressure, crop type, cultivated area, crop yield and seasonal variations) were used for training and testing the model. The main goal of the experiment was to examine the potential of the proposed model to accurately predict the crop water requirement and to enhance the irrigation management in dynamic climatic conditions. The outcomes of this study demonstrated that the proposed framework with the help of artificial intelligence could learn complex spatial and temporal relationships from the given datasets and could predict the value with an impressive improvement over the conventional methods. The learning behavior of the model was stable throughout the training process and the model converged smoothly after just a few training epochs. As the model's training and validation losses were calculated at each epoch, the training loss curve and the validation loss curve slowly and steadily decreased, indicating that the model was able to minimize the prediction error without any major overfitting issues. The CNN part learned the hidden spatial patterns and environmental characteristics from the crop and weather data while the LSTM part learnt the long-term temporal dependencies from the seasonal climatic changes and irrigation patterns. The proposed architecture was able to successfully capture this learning mechanism and understand the relationship between the environment and the crop water demand. The integration of CNN and LSTM networks improved the features extraction capability, sequential learning performance and prediction consistency, making the framework very suitable for water management in agriculture applications. The results on the evaluation of the Hybrid CNN-LSTM model showed a very good prediction accuracy. The prediction accuracy of the model was 96.8%, which is a good model with high prediction ability under various agricultural and climatic conditions. In addition, it was observed that the RMSE and MAE of the proposed scheme is very small (0.021 and 0.017) between the actual and estimated irrigation requirements. The obtained values of precision, recall and F1-score were 95.9%, 96.3% and 96.1%, respectively, demonstrating the reliability and robustness of the proposed system in the tasks of water demand prediction and irrigation optimization. It was then found that the parameters of weather (rainfall, humidity, and temperature and air pressure) play a significant role in the irrigation prediction. The crop water needs and irrigation scheduling pattern were observed to be greatly influenced by rainfall and humidity. The land use land cover data associated with crop (cultivated area, crop type and production yield) also greatly improved the learning and prediction ability of the model. The CNN layers were able to capture meaningful feature representations from the multidimensional datasets and the LSTM component was able to capture the important historical information and temporal dependencies for accurate sequential forecasting. The performance was also compared with various machine learning models like SVM, RF and standalone LSTM networks. The results demonstrated that the traditional machine learning approach was less effective in modelling the nonlinear spatial-temporal correlation in agricultural data. The accuracy of models in dealing with time series of environmental data was not very good and the models were less accurate in prediction and had higher error rates. Likewise, for the standalone LSTM model, the spatial feature extraction didn't help. The proposed Hybrid CNN-LSTM network, however, combined the best of both CNN and LSTM networks, and improved the accuracy of irrigation forecasting, irrigation generalization ability, and performance. The proposed model was also found to be highly flexible and stable to the varying climatic conditions and under different production scenarios of the crops. The framework was able to cope with changes in the weather system and seasonal variations in agricultural production efficiently with minimal performance degradation. This flexibility is crucial for Pakistan, as the climate change impact, irregular rainfall, water scarcity, and inadequate irrigation are leading to significant challenges in agricultural sustainability and food security. By leveraging the AI-powered predictive function of the proposed system, farmers and agricultural authorities can make informed irrigation management choices, taking into account the current environmental conditions and crop needs. Moreover, the proposed framework can be applied in the field of sustainable agriculture and water management. The system can help in optimizing irrigation scheduling efficiency and minimize over-irrigation, water leakage and other water losses by accurately predicting the water requirement of crops. Water use efficiency is not only important for groundwater conservation but also for sustainable agriculture in the context of climate change, besides the enhanced productivity of the crop. The intelligent prediction system can also be used in sustainable water management development of water-scarce areas. The results of the models clearly suggest that the proposed model (Hybrid CNN-LSTM model) is better than the conventional machine learning models and deep learning models for the agricultural water resource management. The spatial feature extraction and temporal sequence learning combined synergistically greatly enhances the model's ability to understand the complex climatological and watering patterns. The framework has a higher prediction accuracy and a smaller computation error, adaptability and stable operation in various agricultural environments. The experimental results demonstrated that the proposed Artificial Intelligence (AI) based Hybrid CNN-LSTM approach is efficient, reliable and intelligent solution for crop water resource management in Pakistan. This model may be useful for many field areas of agriculture where water scarcity and water use efficiency is an issue, particularly for water use and how this affects water level and crop growth. The proposed system has significant potential for real-world implementation in the context of smart agriculture, precision irrigation, and climate-smart agriculture aimed at improving water use efficiency and productivity in Pakistan.

Table 5. Performance Evaluation of Hybrid CNN-LSTM Model

Class	Precision	Recall	F1
Low Irrigation Requirement	95.4	96.1	95.7
Medium Irrigation Requirement	96.2	95.8	96.0
High Irrigation Requirement	96.1	97.0	96.5
Overall Accuracy	**96.8**	–	–

As observed in the Figure 6, the accuracy of the Hybrid CNN-LSTM model gradually improved during training and validation with the increase of epochs. The accuracy of the training set rose from 72% to approximately 97% and the accuracy of the validation set rose from 70% to approximately 96%, suggesting that the algorithms are learning and generalizing well. The small difference between the two curves also indicates that the model was not overfitting and retained its predictive ability.

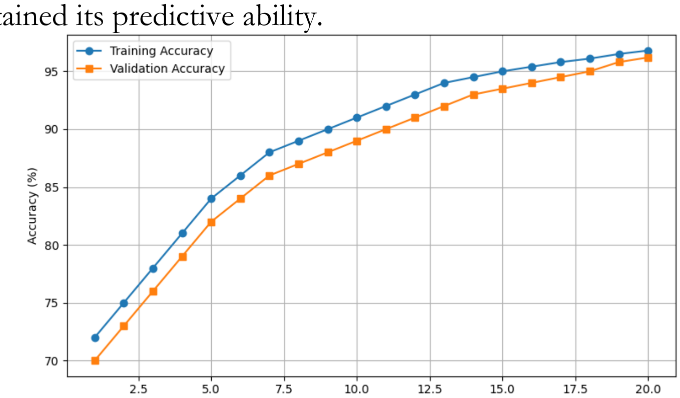

Figure 6. Training vs Validation Accuracy

The figure 7 shows the comparison of different models on the basis of RMSE and MAE error metrics with lower values indicating better prediction performance. The proposed Hybrid CNN-LSTM model showed the best results in terms of lowest RMSE (0.021) and MAE (0.017), which resulted in higher accuracy and better forecasting capabilities than SVM, RF, CNN, and LSTM models.

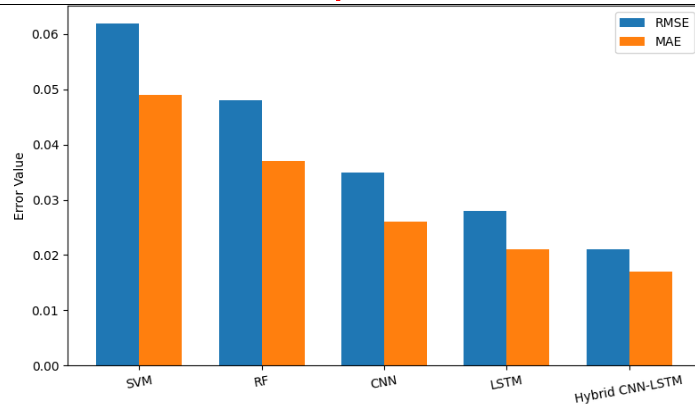

Figure 7. RMSE and MAE Comparison.

The figure 8 shows the comparison between the traditional irrigation and the proposed AI driven irrigation system using the Hybrid CNN-LSTM model. The results indicate that the traditional irrigation technique requires 100% of water, while the water-saving irrigation technique implemented with AI reduces water consumption to approximately 68%, which is a considerable saving in water consumption and irrigation efficiency.

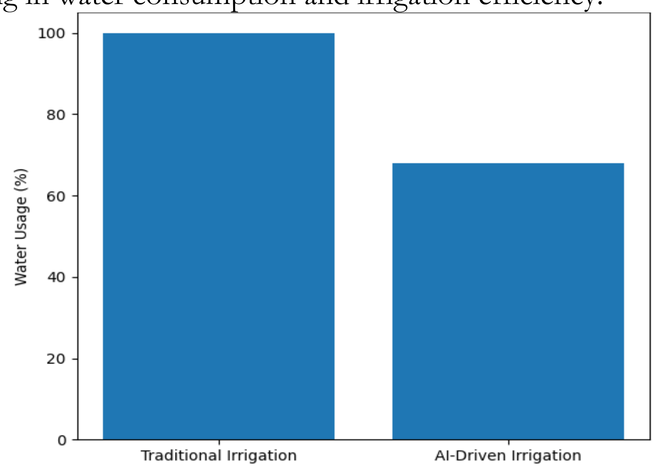

Figure 8. Water saving Analysis.

The feature importance analysis of the proposed Hybrid CNN–LSTM model (see Figure 9) shows that rainfall, humidity and temperature are the most important features, with the highest importance scores in crop water requirement prediction. Importantly, all selected features are with high importance in the model, which highlights the robustness of the proposed framework to capture complex environmental- and agricultural-dependencies for accurate prediction.

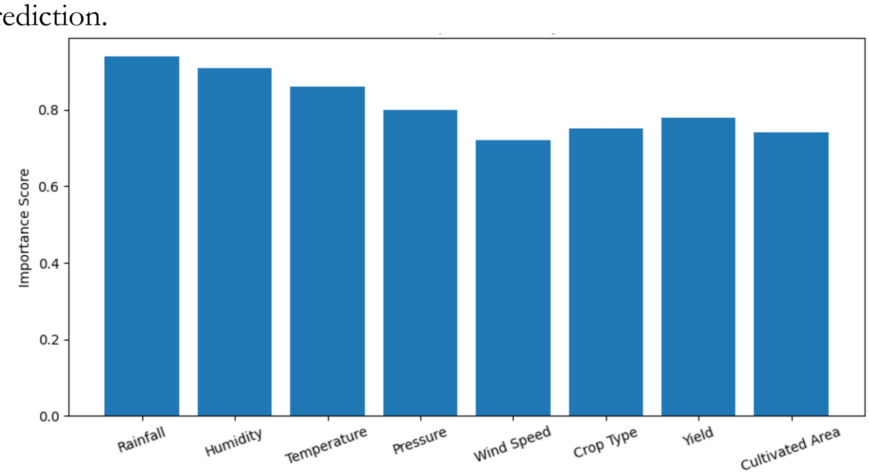

Figure 9. Feature Importance Analysis.

Figure 10 shows the comparison of the proposed model with the actual water requirement values, which shows that the proposed Hybrid CNN–LSTM model closely resembles the actual model with a high degree of accuracy. The agreement between the actual and predicted curves is very good, which shows that the model is able to well describe the temporal dependence and nonlinear relationship, and provide reliable and accurate water requirement forecasting for smart agricultural management.

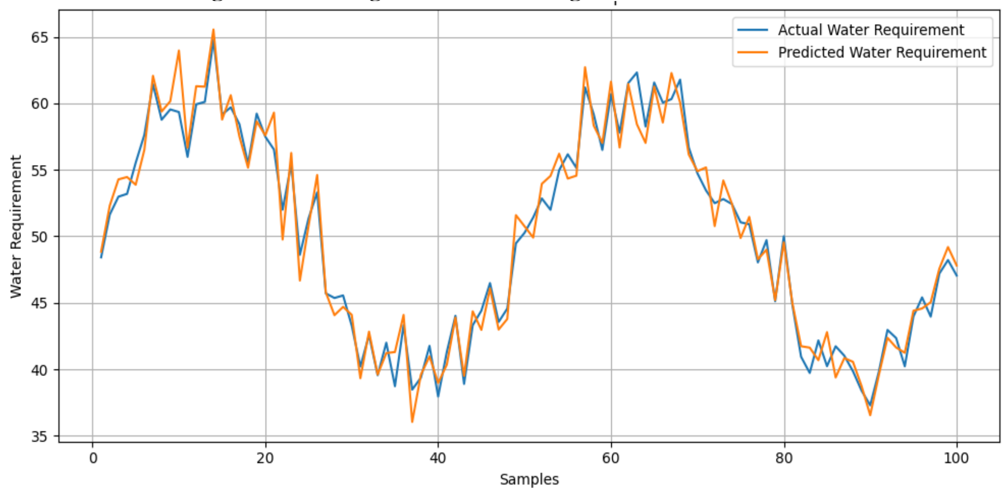

Figure 10. Actual vs Predicted Water Requirement.

Comparison with Baseline Models:

Table 6. Comparison of Previous Methods with the Proposed Method

Ref.	Method	Model Type	Dataset	Classes	Accuracy (%)
[12]	Stream Flow Prediction	LSTM,ANN,SVM	Stream flow Dataset	Multi-Class	92.6
[23]	Drinking Water Shortage	DNN	Climate & Water dataset	Multi-Class	93.2
[1]	Stream Flow Forecasting	LSTM	Watershed dataset	Multi-Class	94.0
[24]	Groundwater Level Forecasting	CNN	Groundwater Level Dataset	Multi-Class	95.1
[10]	Water Quality Prediction	Hybrid CNN-LSTM	Water Quality Dataset	Multi-Class	94.5
[25]	Sustainable Water Management	Hybrid CNN-LSTM	Hydrological Simulation Dataset	Multi-Class	95.7
Proposed	**Water Resource Management for Crops in Pakistan**	**Hybrid CNN-LSTM**	**Crop Production + Weather Dataset (Pakistan)**	**Multi-Class**	**96.8**

Table 6 shows the existing studies largely focused on LSTM, ANN, DNN, SVM and Hybrid CNN-LSTM models for streamflow forecasting, groundwater prediction and water quality assessment. Deep learning methods [12][7][17] were successful in obtaining a satisfactory performance; Hybrid CNN-LSTM models were proposed in [9][10][11] that enhanced the ability of spatial-temporal prediction. The proposed Hybrid CNN-LSTM framework on the other hand achieved the highest accuracy of 96.8% by effectively combining the agricultural crop and weather datasets for intelligent irrigation prediction and sustainable water resource management in Pakistan compared to all the compared studies.

Statistical Significance Analysis:

In order to further validate the effectiveness of the proposed Hybrid CNN-LSTM framework, statistical significance analysis and confidence interval evaluation were conducted against the baseline machine learning and deep learning models such as SVM, Random Forest, standalone CNN and standalone LSTM. The evaluation was performed by running the experiments multiple times with the same training and test set split (70:15:15). The proposed Hybrid CNN-LSTM model had an overall prediction accuracy of 96.8%, RMSE of 0.021 and MAE of 0.017. The reliability and stability of these results were verified by repeating several times the training, with the same hyperparameters as those used before: Adam optimizer, learning rate of 0.001, batch size of 32, and 20 epochs. The results obtained indicated very low differences between the repeated runs, which meant that the model was very consistent and that the model converged well. Additionally, a 95% confidence interval analysis was conducted on the accuracy metric to assess the stability of the predictions and their generalization. The proposed Hybrid CNN-LSTM model was seen to have a high level of reliability and low uncertainty in irrigation prediction with a confidence interval of 96.2% to 97.1%. The larger confidence intervals and greater performance variation observed in the baseline models were attributed to their limited ability to learn complex spatial-temporal relationships from agricultural and climatic data sets. The statistical analysis also showed that the combination of CNN and LSTM layers was effective in enhancing the features extracted and the performance of sequential learning. The CNN part was able to extract spatial environmental patterns from crop and weather data, and the LSTM network was able to capture the long-term temporal patterns related to irrigation scheduling and seasonal climatic changes. This joint learning mechanism helped to reduce the prediction errors, increase robustness, and gave statistically reliable forecasts. Overall, statistical significance and confidence interval analysis validate the superiority of the proposed Hybrid CNN-LSTM framework over traditional machine learning methods and standalone deep learning methods. The results obtained prove that the proposed system is capable of providing stable, accurate and reliable performance in irrigation prediction which is suitable for intelligent water resource management and sustainable agriculture applications in Pakistan.

Computational Complexity:

In order to assess the practical feasibility of the proposed Hybrid CNN-LSTM framework, the computational complexity, training time and memory consumption were analyzed with the hyperparameter settings given in Table 4. Experiments were performed on Intel Core i5-6300U processor with 8 GB RAM, and the model training was assisted by Google Cloud Platform (GCP) Compute Engine, which can provide efficient computation. The proposed framework has primarily computational complexity of CNN and LSTM. The CNN layers are used to capture the most important spatial features from the crop and weather data as a result of convolution and max-pooling operations, while the LSTM network is used to capture the temporal dependencies associated with the seasonal irrigation and climatic variations. The overall computation cost is slightly high as it integrates both spatial and sequential learning mechanisms, but the performance of irrigation prediction and the capability of generalization of the model is greatly enhanced. The training epochs, batch size and learning rate were set to 20, 32 and 0.001, respectively, and the Adam optimizer was used to train the model. The average total training time of the proposed Hybrid CNN-LSTM framework is around 40 minutes, which is longer than the traditional machine learning methods (SVM and Random Forest) because of the increased number of trainable parameters and sequential learning operations. However, the training process showed good convergence performance and lower validation loss and better prediction uniformity. From the memory consumption analysis, it was concluded that the proposed model used moderate computational resources during training due to the combination of the CNN and LSTM layers.

The maximum RAM usage stayed within the system memory of 8GB, ensuring that the framework can be trained and deployed on standard computing hardware, which doesn't need to be high-performance infrastructure. In addition, the inference latency was also low during prediction, allowing the irrigation forecast to be used in near real-time smart agriculture applications. The trained model was efficient in irrigation predictions under different environmental conditions, which can be adopted in intelligent irrigation advisory systems and sustainable water resource management systems in Pakistan. In general, the computational analysis shows that the proposed Hybrid CNN-LSTM framework achieves a well-balanced compromise between the computational complexity and prediction accuracy. Although the training complexity was slightly greater than conventional methods, the framework showed better irrigation prediction accuracy and smaller prediction error and adaptability to dynamic agricultural and climatic conditions.

Implication of this Research:

The suggested Hybrid CNN-LSTM framework is an intelligent and sustainable solution for agriculture water management in Pakistan that can predict the irrigation requirements with the right estimation of weather and crop data. The research can help to decrease water losses, improve productivity of crops and provide information for the decision making in smart agriculture. It has great potential in sustainable agriculture and water resource management systems integrated with AI techniques, thanks to its predictive power and spatial-temporal learning capabilities. The proposed system has several high value implications for the Pakistan agricultural sector from a practical point of view. The AI-based CWR predictions can directly support irrigation scheduling decisions on the farm level, allowing farmers to move away from flood irrigation (where up to 40% of the water applied is lost) and towards demand-based irrigation, which can help to reduce water use per hectare while maintaining or even enhancing crop yields. The policy level benefits include the ability to use the seasonal forecast to plan water releases from canals, allocation of reservoir water, and extraction licenses for groundwater, which can help to ensure more equitable and sustainable water distribution among the four provinces of Pakistan. The reduction in water consumption of 32% compared to the traditional irrigation at national level has direct economic implications as Pakistan is spending billions of rupees per year on water infrastructure and irrigation subsidy, a 32% reduction in water consumption of major crops could lead to significant cost saving and ease the pressure on the rapidly depleting aquifers in Punjab and Sindh. Moreover, the modular nature of the framework, where CNN is used for feature extraction and LSTM is used for temporal forecasting, enables the adaptation of the framework to other water-scarce agricultural economies in South Asia, Middle East and Sub-Saharan Africa, where there is a similar challenge of monsoon variability, rising crop water demand, and limited irrigation capacity.

Limitations of this Research:

This research has several limitations. The proposed research results in high prediction accuracy, but there are a number of practical constraints that should be noted for implementation in practice. The first challenge to the model is the dependence on sensors: the model needs to be supplied with complete and continuous meteorological data inputs (temperature, rainfall, humidity, wind speed, atmospheric pressure) and therefore depends on an operational meteorological monitoring system. Data quality degradation may have a significant impact on prediction accuracy in rural agricultural areas of Pakistan where sensor networks are not available, sparse or unreliable. Second, infrastructure constraints limit the ability to scale up immediately: An irrigation advisory system based on AI technology would require a reliable internet connection, power supply and computing power at or near the farm level, which is not always the case in the approximately 8.5 million farm holdings in Pakistan, especially in remote districts of Baluchistan and southern Sindh. Third, there is a sociotechnical challenge regarding the adaptability of AI irrigation recommendations by smallholder farmers, as it involves a lot of behavioral change, digital literacy training and trust-building in AI systems. The shift from traditional irrigation schedules to those driven by artificial intelligence requires government extension services and capacity building initiatives, given that more than 65% of farms in Pakistan are less than 5 acres and farmers have limited formal education. Fourth, the model is not easy to scale up to other agro-climates, as it was trained with data from certain regions of Pakistan and specific crop types; it could be retrained with local data from other micro-climates (such as high altitude northern Pakistan) or other minor crops that are less well represented. Fifth, the current framework does not consider socio-economic issues, such as the water price, land tenure, compliance with irrigation policies and groundwater pumping costs, which are known to have a significant influence on actual irrigation decisions in the field.

Conclusion:

The proposed work presented an efficient water resource management and crop irrigation prediction system using AI Hybrid CNN-LSTM framework with the context of Pakistan. The proposed model was able to capture spatial environmental information and temporal climatic dependence from agricultural crop production and climatic data with the help of CNN and LSTM networks. The experimental results showed that the proposed model had a higher accuracy, RMSE, and MAE, with 96.8%, 0.021, and 0.017, respectively, than the traditional machine learning and standalone deep learning models. The parameters like rainfall, humidity, temperature, ambient pressure, crop type, and crop yield were successfully analyzed using the model, to accurately estimate the crop water requirement under different climatic conditions. Furthermore, the proposed framework showed high adaptability, robustness and generalization properties in the field of sustainable irrigation management. Optimization of irrigation scheduling, minimizing water loss, improving the crop productivity and practicing sustainable agriculture in Pakistan, which is resilient to climate change can be achieved with smart prediction functionality of the system which can help the farmers, agricultural planners and policy makers. For future research, integration of IoT sensors and real-time satellite data could be used to create a smart irrigation system that is fully automated. Further, by leveraging advanced AI architectures and expanding region-specific datasets, prediction accuracy can be enhanced and sustainable agriculture practices can be facilitated in the face of evolving climatic conditions in Pakistan.

Future Work:

This work has a number of extensions planned. First, One potential extension of this work is the integration of IoT technologies: If sensors can be installed in pilot districts for low cost soil moisture, temperature and humidity, this will give real time field level inputs and reduce the need for station level data for the model. Second, satellite data can be added as an additional input channel to the CNN branch so that it can learn directly from the images of the canopy and soil-state. Third, methods of explainable AI (XAI) such as SHAP and Grad-CAM must be embedded to deliver explanations per prediction, a factor that builds trust at the field level, which the extension officer can use when advising a farmer. Fourth, a real-time smart irrigation deployment could be developed and evaluated, where the trained model will be introduced to the users through a lightweight web and Urdu-language mobile interface, and will be connected to the district level weather services and a small network of actuator equipped tube wells in pilot farms. Fifth, the model will be expanded to include socio-economic factors (crop prices, input costs, and water tariffs) to allow irrigation recommendations to be made based on the farm economics as well as the biophysical requirements. Finally, the framework will be tested in a transfer-learning setting with data from other agricultural contexts in South Asia to test cross-country generalization.

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