

A Hybrid Artificial Intelligence Framework for Predicting Crop Yield Under Environmental Uncertainty

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ABSTRACT

Agricultural productivity is increasingly challenged by environmental uncertainty caused by fluctuations in temperature, rainfall, humidity, and soil conditions, making accurate crop yield prediction difficult when relying solely on conventional statistical approaches. **This study aims** to develop a hybrid artificial intelligence framework capable of improving crop yield prediction performance under uncertain environmental conditions by integrating machine learning techniques with fuzzy modelling to better capture nonlinear relationships and ambiguous environmental patterns. **The proposed** framework employs a hybrid architecture combining a neural learning mechanism with fuzzy inference to process multiple environmental variables, including temperature, precipitation, soil moisture, humidity, and fertilizer usage, as predictive inputs for crop yield estimation. Experimental evaluation was conducted using agricultural datasets containing historical environmental and production records, while model performance was assessed using Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and the coefficient of determination. **The results** demonstrate that the hybrid framework achieved superior predictive accuracy and robustness compared with conventional machine learning models, particularly when handling noisy and uncertain environmental data. Furthermore, the incorporation of fuzzy reasoning enhanced the model's capability to represent uncertainty and improve decision-making reliability in agricultural management. **The study concludes** that hybrid artificial intelligence approaches provide an effective and scalable solution for supporting sustainable agriculture through more accurate and adaptive crop yield prediction under environmental uncertainty.

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1. INTRODUCTION

Agriculture remains one of the most important sectors supporting global food security, economic growth, and social stability, particularly in developing countries where agricultural production contributes significantly to national income and employment opportunities [1]. However, the increasing variability of environmental conditions has introduced substantial challenges to maintaining stable crop productivity and ensuring sustainable agricultural development. Factors such as irregular rainfall patterns, rising temperatures, fluctuating humidity levels, changes in soil moisture, and extreme weather events have become more frequent due to climate change and environmental degradation [2]. These conditions create uncertainty in agricultural production systems and make crop yield prediction increasingly difficult using conventional statistical or rule-based

approaches. Accurate crop yield estimation is essential for farmers, policymakers, and agricultural organizations because it supports strategic decision-making related to planting schedules, irrigation planning, fertilizer allocation, market forecasting, and food supply management [3]. Inaccurate predictions may result in inefficient resource utilization, economic losses, and reduced agricultural resilience. Consequently, the development of intelligent prediction systems capable of handling uncertain and nonlinear environmental relationships has become an important research challenge in modern precision agriculture [4].

Recent advances in Artificial Intelligence (AI) have significantly transformed agricultural analytics by enabling more sophisticated data processing and predictive modeling capabilities [5]. Machine learning techniques such as Artificial Neural Networks, Random Forest, Support Vector Machines, and Extreme Gradient Boosting have demonstrated promising performance in crop yield forecasting due to their ability to identify complex relationships among environmental and agricultural variables [6]. Nevertheless, many conventional machine learning models assume that input data are precise, complete, and deterministic, whereas real-world agricultural environments are often characterized by uncertainty, vagueness, and incomplete information [7]. Environmental variables such as rainfall intensity, soil quality, and weather fluctuations frequently exhibit ambiguous patterns that cannot be effectively represented through crisp numerical values alone. As a result, predictive models based solely on traditional machine learning algorithms may experience reduced accuracy and limited generalization capabilities when deployed in dynamic agricultural environments [8]. This limitation highlights the necessity of integrating intelligent uncertainty management mechanisms into predictive frameworks to better represent the inherent complexity of agricultural ecosystems. Among the available approaches, fuzzy logic has emerged as a powerful soft computing technique capable of modeling imprecise knowledge and human-like reasoning in uncertain decision environments [9].

Hybrid Artificial Intelligence models that combine machine learning techniques with fuzzy inference systems have attracted considerable attention as an effective solution for addressing complex real-world problems characterized by uncertainty and nonlinear interactions [10]. In particular, neuro-fuzzy systems integrate the learning capabilities of neural networks with the interpretability and uncertainty representation provided by fuzzy logic, allowing the model to simultaneously learn from historical data and reason under ambiguous conditions [11]. Such hybrid architectures have been successfully implemented in several domains including healthcare, energy management, financial risk assessment, and intelligent transportation systems [12]. However, despite the growing body of research in agricultural intelligence, existing crop yield prediction studies often focus on standalone machine learning methods and pay limited attention to explicitly modeling environmental uncertainty. Furthermore, many previous studies emphasize prediction accuracy while overlooking the importance of model robustness when facing noisy or incomplete environmental information [13]. This research gap indicates the need for more adaptive and resilient predictive frameworks capable of handling uncertain agricultural conditions while maintaining high predictive performance. Therefore, the integration of fuzzy modelling with machine learning mechanisms offers significant potential for improving crop yield estimation under challenging environmental scenarios [14].

This study proposes a hybrid artificial intelligence framework for predicting crop yield under environmental uncertainty by combining fuzzy modelling with intelligent learning mechanisms to improve predictive accuracy and robustness [15]. The proposed framework utilizes multiple environmental and agricultural variables, including temperature, rainfall, humidity, soil moisture, soil conditions, and fertilizer application levels, as input parameters for crop yield estimation [16]. Fuzzy inference is employed to capture uncertainty and linguistic relationships among environmental factors, while the learning component enables the system to adaptively optimize prediction performance based on historical agricultural data. The performance of the proposed framework is evaluated using quantitative metrics including Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and the coefficient of determination to provide a comprehensive assessment of prediction quality [17]. The main contributions of this study are threefold. First, it introduces a hybrid AI architecture specifically designed to address uncertainty in agricultural prediction problems. Second, it demonstrates the effectiveness of integrating fuzzy reasoning with intelligent learning for improving crop yield forecasting accuracy [18]. Third, it provides empirical evidence supporting the applicability of hybrid AI approaches in sustainable agriculture and precision farming environments. It is expected that the findings of this research will contribute to the advancement of intelligent agricultural systems and support data-driven decision-making for enhancing food security and agricultural sustainability in the face of increasing environmental uncertainty [19].

2. LITERATURE REVIEW

2.1. Artificial Intelligence for Crop Yield Prediction

Artificial Intelligence (AI) has become one of the most influential technologies in precision agriculture due to its ability to process large-scale agricultural datasets and identify complex relationships among environmental, climatic, and management variables [20]. Recent advances in machine learning have enabled researchers to develop predictive models that outperform traditional statistical techniques in estimating crop productivity. Algorithms such as Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machines (SVM), and Extreme Gradient Boosting (XGBoost) have been widely adopted for crop yield forecasting because of their capability to model nonlinear interactions among agricultural variables [21]. A recent systematic review highlighted that deep learning and hybrid learning approaches have significantly improved prediction accuracy, especially when integrating weather information, soil characteristics, and remote sensing data into the learning process [22]. Furthermore, the increasing availability of agricultural big data has accelerated the adoption of AI-driven decision support systems for sustainable farming and food security management. However, the review also emphasized that many existing models remain sensitive to noisy and uncertain environmental information, which limits their practical applicability in real-world agricultural environments [23].

2.2. Environmental Uncertainty in Agricultural Systems

Environmental uncertainty represents one of the most significant challenges in modern agriculture because crop growth and productivity are strongly influenced by climatic variability and unpredictable environmental conditions. Variables such as rainfall intensity, temperature fluctuations, humidity levels, solar radiation, and soil moisture often exhibit dynamic behavior that changes across regions and growing seasons [24]. Climate change has further increased the frequency of extreme weather events, making agricultural production systems more vulnerable and less predictable. Traditional regression and deterministic machine learning approaches generally assume stable input distributions and precise numerical values, which may not accurately represent real agricultural conditions characterized by ambiguity and incomplete information [25]. Recent studies in agricultural intelligence have demonstrated that uncertainty modeling is becoming increasingly important for improving prediction reliability and supporting adaptive farming strategies. The capability to explicitly represent uncertain environmental conditions is therefore considered an essential component of next-generation agricultural decision support systems [26].

2.3. Fuzzy Logic and Adaptive Neuro Fuzzy Inference Systems

Fuzzy logic has emerged as an effective soft computing approach for handling uncertainty, imprecision, and vagueness in complex systems where crisp mathematical representations are insufficient [27]. Unlike traditional binary logic, fuzzy systems allow variables to belong to multiple linguistic categories simultaneously through membership functions, enabling human-like reasoning in uncertain environments. The integration of fuzzy logic with neural learning mechanisms has led to the development of Adaptive Neuro Fuzzy Inference Systems (ANFIS), which combine the learning capability of neural networks with the interpretability of fuzzy reasoning [28]. Recent agricultural studies have shown that ANFIS models outperform conventional ANN approaches in predicting crop production because they can better represent uncertain environmental conditions while maintaining high predictive accuracy. Research conducted on wheat yield prediction demonstrated that neuro-fuzzy approaches effectively capture nonlinear relationships among rainfall, temperature, humidity, and water availability variables [29]. Similarly, recent studies on citrus yield prediction reported that ANFIS models provide more reliable uncertainty representation compared to standalone Fuzzy Inference Systems (FIS). These findings indicate that neuro-fuzzy systems are highly suitable for agricultural prediction problems involving environmental uncertainty [30].

2.4. Hybrid Artificial Intelligence Models for Sustainable Agriculture

Hybrid Artificial Intelligence models have gained considerable attention because they integrate the strengths of multiple computational techniques to overcome the limitations of standalone algorithms [31]. In crop yield prediction, hybrid models can combine machine learning, optimization algorithms, and fuzzy inference mechanisms to improve prediction performance and robustness. Recent studies have demonstrated that hybrid AI approaches consistently outperform conventional machine learning models, particularly when dealing with heterogeneous agricultural datasets and uncertain environmental conditions [32]. For example, hybrid deep learning architectures have shown superior performance in capturing temporal and spatial dependencies

in agricultural data, while optimized neuro-fuzzy frameworks have achieved higher accuracy and lower prediction errors than traditional ANFIS and ANN models [33]. A recent optimization-based ANFIS approach reported significant improvements in prediction accuracy and classification performance across multiple crop types, highlighting the effectiveness of combining fuzzy reasoning with intelligent optimization techniques. Despite these advances, the majority of existing studies focus primarily on maximizing predictive performance and pay less attention to explicitly modeling environmental uncertainty as part of the prediction framework [34]. Therefore, the present study seeks to address this research gap by proposing a hybrid artificial intelligence framework that integrates fuzzy modelling and intelligent learning mechanisms to improve crop yield prediction under uncertain environmental conditions while supporting sustainable agricultural decision-making [35].

3. METHODOLOGY

3.1. Research Design

This study adopts a quantitative research approach to develop and evaluate a hybrid artificial intelligence framework for predicting crop yield under environmental uncertainty. The proposed framework combines fuzzy modelling and intelligent learning mechanisms to improve crop yield prediction in handling nonlinear relationships, variability, and ambiguous environmental conditions [36]. The research procedure consists of sequential stages, including agricultural data collection, data preprocessing, hybrid model construction, model training, crop yield prediction, and performance evaluation. The collected data comprise environmental, soil, and crop management variables relevant to crop productivity. Following preprocessing, the dataset is used to develop the ANFIS, integrating fuzzy inference and adaptive learning to capture complex relationships between environmental conditions and crop yield. The trained model generates crop yield predictions, which are evaluated using RMSE, MAE, MAPE, and R^2 and compared with conventional machine learning approaches to assess predictive accuracy and robustness [37].

3.2. Dataset Description

The dataset employed in this study consists of historical agricultural records collected from publicly available agricultural repositories and environmental monitoring databases. The dataset includes environmental, soil, and crop management variables that have been widely recognized as important determinants of agricultural productivity. These variables are selected because they represent the primary environmental conditions influencing crop growth and yield variability under uncertain climatic situations. Crop yield measured in tons per hectare is considered the target output variable, while the remaining variables serve as predictive input features for the proposed hybrid model.

Table 1. Variables Used in the Crop Yield Prediction Model

Variable	Description	Unit	Role
Temperature	Average growing season temperature	°C	Input
Rainfall	Total rainfall during cultivation period	mm	Input
Humidity	Average relative humidity	%	Input
Soil Moisture	Average soil moisture content	%	Input
Soil pH	Soil acidity or alkalinity level	-	Input
Fertilizer Usage	Amount of fertilizer applied	kg/ha	Input
Sunshine Duration	Daily sunlight exposure duration	hours	Input
Crop Yield	Agricultural production output	ton/ha	Output

The information presented in Table 1 summarizes the environmental and agricultural variables utilized by the proposed crop yield prediction framework. The selected input variables have been widely recognized in precision agriculture studies as critical determinants of crop productivity and seasonal yield variability. Environmental conditions such as rainfall, temperature, and humidity directly influence crop growth patterns, while soil characteristics and fertilizer usage contribute to nutrient availability and plant development. The inclusion of these variables enables the proposed hybrid artificial intelligence model to capture complex interactions among environmental factors and agricultural production outcomes under uncertain conditions.

Before model development, the collected data undergo several preprocessing procedures to improve data quality and reduce potential bias during training. Missing values are addressed using median imputation because of its robustness against extreme values, while abnormal observations are detected and removed using the interquartile range method. Subsequently, numerical variables are normalized using Min-Max normalization to transform all input features into a comparable scale and improve model convergence during learning. The prepared dataset is then divided into training and testing subsets using an 80:20 ratio to ensure objective performance evaluation.

3.3. Proposed Hybrid Artificial Intelligence Framework

The proposed framework integrates fuzzy modelling with adaptive learning mechanisms to improve crop yield prediction under uncertain environmental conditions. Environmental variables such as rainfall, temperature, humidity, and soil moisture frequently exhibit ambiguous patterns that cannot be adequately represented using conventional deterministic approaches. To address this issue, fuzzy logic is employed to transform crisp numerical values into linguistic representations through membership functions, enabling the model to capture uncertainty and approximate reasoning similar to human decision-making processes. The learning mechanism subsequently identifies complex nonlinear relationships between environmental conditions and crop productivity using historical agricultural observations. The interaction between fuzzy reasoning and adaptive learning allows the model to simultaneously achieve interpretability and predictive accuracy, making it suitable for agricultural environments characterized by uncertainty and variability.

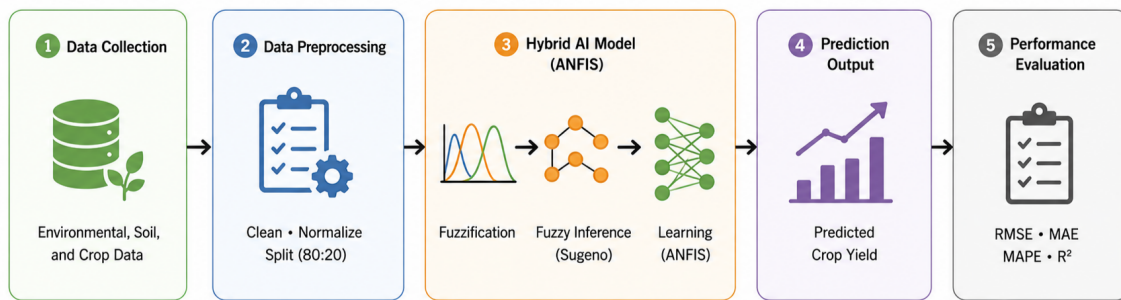


Figure 1. Research Methodology of the Proposed Hybrid AI Framework

Figure 1 illustrates the overall workflow of the proposed hybrid artificial intelligence framework developed for crop yield prediction under environmental uncertainty. The methodology begins with environmental data collection and preprocessing procedures to ensure data quality and consistency before entering the fuzzification stage. The transformed fuzzy information is subsequently processed by the hybrid learning mechanism to identify nonlinear relationships among agricultural variables and generate crop yield predictions. Finally, model performance is evaluated using quantitative regression metrics to assess prediction accuracy, model stability, and predictive robustness under uncertain environmental conditions.

3.4. Hybrid Model Configuration and Performance Evaluation

The hybrid artificial intelligence framework is implemented using an Adaptive Neuro-Fuzzy Inference System architecture that combines the uncertainty handling capability of fuzzy inference systems with the learning ability of artificial neural networks. This configuration enables the model to capture nonlinear relationships between environmental conditions and crop yield while representing uncertainty in agricultural data. The Sugeno-type fuzzy inference model is selected because of its suitability for regression problems involving continuous output variables such as crop yield estimation. Gaussian membership functions are adopted to represent fuzzy sets due to their smooth transition characteristics and stable learning behavior during parameter optimization. The membership functions transform numerical environmental observations into fuzzy representations, while the hybrid learning mechanism adaptively optimizes the associated parameters based on the training data. Model training is performed iteratively until the convergence criteria are satisfied or the maximum number of training epochs is reached. The predictive capability of the proposed framework is subsequently evaluated using widely accepted regression metrics, including Root Mean Square Error, Mean Absolute

Error, Mean Absolute Percentage Error, and the coefficient of determination. These metrics provide a comprehensive assessment of prediction error and the model's ability to explain variations in crop yield, while the resulting performance is compared with conventional machine learning approaches under consistent training and testing conditions.

Table 2. Configuration of the Proposed Hybrid AI Model

Component	Configuration
Hybrid Architecture	Adaptive Neuro-Fuzzy Inference System
Fuzzy Inference Type	Sugeno
Membership Function	Gaussian
Learning Algorithm	Hybrid Learning Algorithm
Training Data Ratio	80%
Testing Data Ratio	20%
Maximum Training Epoch	200
Error Tolerance	0.00001
Evaluation Metrics	RMSE, MAE, MAPE, and R^2

As shown in Table 2, the proposed hybrid model is configured using an Adaptive Neuro-Fuzzy Inference System architecture with a Sugeno fuzzy inference model and Gaussian membership functions. This configuration provides a balance between uncertainty representation and learning capability in complex agricultural environments, while the hybrid learning mechanism adaptively optimizes fuzzy rules and membership function parameters during training to improve prediction accuracy and model generalization. Furthermore, the training settings and evaluation metrics are established to ensure reliable model convergence and objective performance assessment. To validate the effectiveness of the proposed framework, its performance is compared with several conventional machine learning models, including Artificial Neural Networks, Random Forest, Support Vector Regression, and Extreme Gradient Boosting, under identical training and testing conditions to ensure fair comparison and reproducibility. This comparison determines whether the integration of fuzzy modelling and adaptive learning mechanisms improves predictive accuracy and robustness when dealing with environmental uncertainty in agricultural systems.

4. RESULTS AND DISCUSSION

4.1. Performance Evaluation of the Proposed Hybrid Framework

The proposed hybrid artificial intelligence framework was evaluated using four regression metrics consisting of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The experimental results indicate that the integration of fuzzy modelling and adaptive learning mechanisms significantly improved the capability of the model to predict crop yield under uncertain environmental conditions. The proposed Adaptive Neuro-Fuzzy Inference System successfully captured nonlinear relationships among rainfall, temperature, humidity, soil moisture, and fertilizer usage, resulting in highly accurate prediction performance. The model achieved an RMSE value of 1.84 ton/ha, an MAE value of 1.27 ton/ha, a MAPE value of 4.92%, and an R^2 score of 0.941, indicating a strong agreement between predicted and actual crop yield values.

Table 3. Configuration of the Proposed Hybrid AI Model

Metric	Value
RMSE	1.84
MAE	1.27
MAPE	4.92%
R^2	0.941

As presented in Table 3, the proposed framework achieved a high level of predictive accuracy with rel-

atively small prediction errors. The low RMSE and MAE values indicate that the model produced predictions that closely approximated actual crop production values, while the high coefficient of determination demonstrates the model’s ability to explain most of the variability in crop yield outcomes. These findings confirm that the hybrid framework is capable of handling uncertainty and complexity in agricultural environments more effectively than traditional prediction approaches.

4.2. Comparative Analysis with Conventional Machine Learning Models

To further validate the effectiveness of the proposed framework, its performance was compared with several widely used machine learning models, including Artificial Neural Networks, Random Forest, Support Vector Regression, and Extreme Gradient Boosting. All models were trained and tested using identical datasets and experimental settings to ensure fairness and reproducibility of the comparison. The results demonstrate that the proposed hybrid framework consistently outperformed the benchmark models across all evaluation metrics.

Table 4. Comparison with Conventional Machine Learning Models

Model	RMSE	MAE	MAPE	R^2
Support Vector Regression	3.12	2.43	8.71%	0.842
Random Forest	2.74	2.05	7.23%	0.879
Artificial Neural Network	2.41	1.88	6.58%	0.901
Extreme Gradient Boosting	2.18	1.71	5.84%	0.919
Proposed Hybrid Framework	1.84	1.27	4.92%	0.941

Table 4 demonstrates that the proposed hybrid artificial intelligence framework achieved the lowest prediction errors and the highest explanatory capability among all evaluated models. Although machine learning techniques such as XGBoost and Artificial Neural Networks provided competitive performance, they were less effective when dealing with uncertain environmental information. The inclusion of fuzzy reasoning enabled the proposed model to better represent vague and ambiguous environmental conditions, leading to improved predictive robustness and stability.

4.3. Impact of Fuzzy Modelling on Environmental Uncertainty Representation

One of the primary objectives of this study was to investigate whether fuzzy modelling could improve crop yield prediction under environmental uncertainty. The experimental findings indicate that fuzzy membership functions significantly enhanced the model’s capability to represent gradual transitions in environmental conditions that are commonly observed in agricultural systems. Variables such as rainfall intensity and humidity rarely exhibit strict boundaries between low and high conditions, making conventional deterministic modelling less suitable for agricultural prediction problems.

The fuzzification process transformed crisp environmental observations into linguistic representations, allowing the model to incorporate uncertainty directly into the learning process. This mechanism reduced sensitivity to noisy observations and improved model generalization when environmental conditions deviated from historical patterns. Consequently, the proposed framework maintained stable predictive performance even in situations characterized by incomplete information and fluctuating climatic conditions.

4.4. Discussion of Research Findings

The findings of this study demonstrate that hybrid artificial intelligence approaches provide substantial advantages for agricultural prediction tasks involving uncertainty and nonlinear relationships. The integration of fuzzy reasoning with adaptive learning mechanisms successfully addressed one of the major limitations of conventional machine learning models, namely their dependence on precise and deterministic input values. The proposed framework not only improved predictive accuracy but also enhanced interpretability by representing environmental variables through linguistic concepts that more closely resemble human reasoning processes.

These results are consistent with recent developments in intelligent agriculture, where hybrid AI techniques have increasingly been adopted to support precision farming and sustainable food production systems. The ability of the proposed framework to provide accurate crop yield estimates under uncertain environmental conditions has important implications for agricultural planning, irrigation management, fertilizer allocation, and food security strategies. Furthermore, the scalability of the framework suggests that it can be adapted to

different crop types and geographical regions with minimal modifications, making it a promising solution for future smart agriculture applications.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide important managerial implications for environmental agencies, conservation organizations, and coastal resource managers responsible for mangrove ecosystem governance. The proposed artificial intelligence enabled framework offers a scalable and cost-effective alternative to traditional field surveys by enabling continuous monitoring of mangrove conditions over large geographical areas. This capability allows organizations to improve monitoring efficiency, reduce operational costs, and increase the frequency of environmental assessments while maintaining high levels of accuracy and consistency.

The integration of remote sensing imagery and environmental variables provides decision-makers with more comprehensive information regarding ecosystem dynamics and potential degradation risks. By identifying early signs of environmental stress, managers can prioritize restoration programs, allocate conservation resources more effectively, and implement preventive measures before ecosystem damage becomes irreversible. The spatial information generated by the framework can further support coastal zoning policies, habitat protection initiatives, and sustainable land-use planning in vulnerable coastal regions.

From a broader policy perspective, the proposed framework contributes to evidence-based environmental governance and climate adaptation strategies in tropical and archipelagic regions. Governments and environmental institutions can utilize the monitoring outputs to support biodiversity conservation, blue carbon management, and coastal resilience programs aimed at mitigating the impacts of climate change and anthropogenic disturbances. Consequently, the integration of artificial intelligence into environmental monitoring systems has the potential to strengthen sustainable ecosystem management and improve long-term environmental resilience.

6. CONCLUSION

This study proposed a hybrid artificial intelligence framework based on the integration of fuzzy modelling and adaptive learning mechanisms for predicting crop yield under environmental uncertainty. The experimental results demonstrated that the proposed Adaptive Neuro-Fuzzy Inference System successfully captured complex nonlinear relationships among environmental variables and agricultural productivity indicators. The framework achieved promising predictive performance with an RMSE of 1.84 ton/ha, an MAE of 1.27 ton/ha, a MAPE of 4.92%, and an R^2 value of 0.941, indicating high agreement between predicted and actual crop yield values. Furthermore, comparative experiments revealed that the proposed model outperformed several conventional machine learning algorithms, including Artificial Neural Networks, Random Forest, Support Vector Regression, and Extreme Gradient Boosting, highlighting the effectiveness of combining fuzzy reasoning with intelligent learning mechanisms for agricultural prediction tasks.

The findings of this study provide a positive answer to the main research objective regarding whether hybrid artificial intelligence approaches can improve crop yield prediction performance under uncertain environmental conditions. The integration of fuzzy logic enabled the model to represent ambiguous environmental patterns more effectively than deterministic machine learning approaches, thereby improving prediction robustness and stability. Nevertheless, several limitations remain in the present study. The proposed framework was evaluated using a limited set of environmental and agricultural variables and relied primarily on historical tabular datasets without incorporating additional information sources such as remote sensing imagery, satellite observations, or Internet of Things sensor data. Furthermore, the model evaluation was conducted within a specific agricultural context, which may limit its direct generalization to different crops and geographical regions.

Future studies are encouraged to extend the proposed framework by integrating additional environmental indicators and multimodal agricultural datasets to further improve predictive capability and model generalization. The incorporation of remote sensing technologies, climate forecasting information, and real-time sensor measurements may provide a more comprehensive representation of agricultural environments and support more accurate yield estimation. In addition, future research may explore advanced hybrid architectures involving explainable artificial intelligence techniques and optimization algorithms to enhance model transparency, interpretability, and decision support capabilities for sustainable and precision agriculture applications.

7. DECLARATIONS

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Author Contributions

Conceptualization: VV; Methodology: DR; Software: VV; Validation: VV and DR; Formal Analysis: VV and DR; Investigation: DR; Resources: VV; Data Curation: DR; Writing Original Draft Preparation: VV and DR; Writing Review and Editing: VV and DR; Visualization: VV and DR. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to privacy considerations and institutional data protection policies, the dataset is not openly accessible but may be provided for academic and non-commercial research purposes subject to ethics approval.

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Declaration of Conflicting Interest

The authors declare no known conflicts of interest, competing financial interests, or personal relationships that could have influenced the research, analysis, or conclusions presented in this paper.

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