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Research Article

Fuzzy Logic and Extreme Learning Machine for Web-Based Agribusiness Crop Recommendation

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Abstract

Crop selection is not only an agronomic problem but also an operational decision in agribusiness because it affects input allocation, production risk, revenue potential, and supply-chain planning. This study develops a web-based crop recommendation system for agribusiness decision support by integrating Fuzzy Logic and Extreme Learning Machine (ELM). Fuzzy Triangular Membership Functions transformed seven crisp agro-environmental variables, namely N, P, K, temperature, humidity, pH, and rainfall, into 21 linguistic membership features. The transformed features were classified using an ELM model with 512 hidden neurons, sigmoid activation, and ridge-regularized analytic learning. The model was evaluated on the Crop Recommendation Dataset containing 2,200 records and 22 crop classes. The proposed Fuzzy-ELM model achieved an accuracy of 0.95, with macro-average precision, recall, and F1-score of 0.95, 0.95, and 0.94, respectively. The model was deployed in a Flask-based dashboard with MySQL storage and real-time weather integration to support practical crop-selection decisions. Black-box testing produced 100% valid results, while User Acceptance Testing reached 97.86%. The findings indicate that fuzzy feature transformation and fast analytic learning can support data-driven agribusiness applications under uncertain soil and climate conditions.

Keywords: Agribusiness decision support, crop recommendation, Extreme Learning Machine, Fuzzy Logic, smart farming

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1. Introduction

Agriculture is increasingly managed as an agribusiness system in which crop choice influences input efficiency, production costs, yield risk, market supply, and farm-level revenue. A wrong crop-selection decision may lead to inefficient fertilizer use, lower productivity, and poor alignment between land characteristics and market-oriented production planning. For this reason, digital decision-support systems are becoming important not only for agricultural production but also for agribusiness management.

In many farming contexts, crop selection is still influenced by experience, habit, seasonal intuition, and informal advice. Such knowledge is valuable, but it may be insufficient when environmental conditions change rapidly or when farmers must choose among many crops with similar soil requirements. Agribusiness actors also face a practical need to document decisions, compare previous recommendations, and communicate results to other stakeholders such as extension officers, input suppliers, farmer groups, and local agricultural service providers. Smart farming provides the technological foundation for this shift by combining sensors, data analytics, artificial intelligence, and web-based applications to support operational decision-making [1], [2]. Recent reviews show that machine learning has been widely applied to crop yield prediction, crop selection, irrigation scheduling, and soil monitoring because it can discover nonlinear patterns from agro-environmental data [3]. In an agribusiness context, these models can support planning decisions by translating soil and climate data into actionable recommendations.

Crop recommendation is a practical decision-support task within digital agribusiness. Instead of predicting yield only after a crop has been selected, a recommendation model assists farmers, agricultural entrepreneurs, and service providers in selecting crops that better match measurable land and environmental conditions. Several recent studies have reported high performance using supervised learning, ensemble models, and explainable machine learning for crop recommendation based on nutrient and climate variables [4], [5], [6], [7]. IoT-enabled systems further demonstrate that real-time soil-nutrient acquisition can connect predictive models to deployable agricultural services [8], [9], [10].

Despite these advances, crop recommendation remains challenging because agribusiness decisions are made under uncertainty. Agro-environmental variables are rarely separable by crisp thresholds. Soil pH,

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temperature, humidity, rainfall, and nutrient concentrations often represent gradual suitability conditions rather than binary states. A pH value, for example, may be partly suitable for one crop but only marginally suitable for another. Fuzzy methods are therefore relevant because they represent uncertain and overlapping conditions through membership degrees rather than rigid class boundaries. A recent systematic review confirms that fuzzy logic remains useful in smart farming because it supports decision-making under vague, imprecise, and sensor-driven agricultural environments [11], while fuzzy-IoT irrigation studies show its practicality in real-time agricultural control [12].

Extreme Learning Machine (ELM) is also attractive for this domain because it trains single-hidden-layer feedforward neural networks through analytic output-weight estimation rather than iterative backpropagation. The original ELM framework offers fast learning and competitive generalization [14], and later work extended it to regression and multiclass classification [15]. However, conventional ELM can be sensitive to the random initialization of hidden-layer parameters and to noisy input representation, so feature transformation and regularization are important for improving stability [16], [17]. From the perspective of applied intelligence, the combination of Fuzzy Logic and ELM is relevant because it joins two complementary strengths. Fuzzy Logic represents uncertain environmental conditions in a form that is closer to human reasoning, while ELM provides a fast classification mechanism suitable for lightweight web deployment. This combination is particularly suitable for small-scale agribusiness systems because the model can be trained efficiently and then embedded into an application without requiring heavy computational infrastructure.

This study addresses the need for a compact, deployable, and interpretable crop recommendation model that effectively handles uncertainty in agricultural data. It proposes a hybrid Fuzzy-ELM approach, where Fuzzy Triangular Membership Functions transform uncertain soil and climate variables into linguistic features before multiclass classification using ELM. The study contributes by (1) applying fuzzy feature engineering, (2) evaluating the model on a 22-class crop recommendation dataset, and (3) deploying it as a web-based decision support system validated through functional and user acceptance testing. The proposed system aims to improve crop selection, reduce trial-and-error planting, and provide a foundation for future integration with agribusiness services.

2. Methods

2.1 Research Design

This study used an experimental software-engineering approach. The experimental component evaluated whether fuzzy feature transformation combined with ELM could produce reliable multiclass crop classification. The software component translated the trained model into a web-based recommendation system intended to support agribusiness decision-making.

The research workflow consisted of six stages: problem identification, dataset preparation, fuzzy feature transformation, ELM model training, system implementation, and system evaluation. Problem identification focused on the need for a practical recommendation tool that can help agribusiness users transform soil and climate parameters into crop-selection decisions. Dataset preparation ensured that the variables used by the model corresponded to common decision variables in crop suitability analysis. The modelling stage examined the predictive capability of Fuzzy-ELM, while the implementation stage assessed whether the trained model could be embedded into a usable web application.

2.2 Dataset and Preprocessing

The dataset used in this study was the Crop Recommendation Dataset from Kaggle [23]. It contains 2,200 records with seven numerical input variables: nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall. The target variable consists of 22 crop classes, including rice, maize, chickpea, kidney beans, pigeon peas, moth beans, mung bean, black gram, lentil, pomegranate, banana, mango, grapes, watermelon, muskmelon, apple, orange, papaya, coconut, cotton, jute, and coffee. The dataset was selected because its feature structure is consistent with the type of soil and climate parameters frequently used in recent crop recommendation studies [4], [5], [18], [19].

Each input variable has a decision meaning in agribusiness crop planning. N, P, and K represent soil nutrient availability and are related to fertilizer planning. pH indicates soil acidity and affects nutrient absorption. Temperature, humidity, and rainfall represent environmental suitability and climate-related production risk. Although the dataset does not include direct economic variables such as selling price, input cost, or land size, these agro-environmental variables form the first layer of agribusiness decision-making because a crop must be technically suitable before economic planning can be meaningful.

The preprocessing stage consisted of data inspection, missing-value checking, duplicate checking, min-max normalization, fuzzy transformation, and train-test splitting. No records were removed during data cleaning,

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so the complete 2,200 observations were retained. Each numerical feature was normalized to the range of $[0,1]$ using the min-max normalization method. Normalization was applied before fuzzy transformation to ensure that variables with different measurement scales contributed comparably to the model.

Table 1. Input Variables and Agribusiness Decision Relevance

Variable	Agribusiness Interpretation
N	Nitrogen availability; supports fertilizer and crop-suitability planning
P	Phosphorus availability; related to root development and input planning
K	Potassium availability; supports plant resilience and quality-related planning
Temperature	Climate suitability and production-risk indicator
Humidity	Environmental suitability and disease-risk-related indicator
pH	Soil acidity; affects nutrient absorption and crop compatibility
Rainfall	Water availability proxy for crop-selection and planting decisions

2.3 Fuzzy Feature Transformation

Fuzzy transformation was performed using Triangular Membership Functions (TMF). For each normalized feature, three linguistic categories were constructed: low, medium, and high. The triangular function maps a crisp value x into a membership degree $\mu(x)$ in the range $[0, 1]$. In general, $\mu(x) = 0$ when $x$is outside the lower or upper bounds, increases linearly between the lower and center points, reaches 1 at the center point, and decreases linearly toward the upper bound. Because seven original variables were each transformed into three membership degrees, the ELM input layer received 21 fuzzy features. This design follows the fuzzy-set principle that partial membership represents uncertain boundaries more effectively than binary classification [13], allowing gradual transitions between categories to be captured without imposing strict decision thresholds.

In this study, fuzzy transformation was used as feature engineering rather than as a standalone rule-based inference system. This distinction is important. Traditional fuzzy decision systems often rely on manually designed IF-THEN rules, while the present system uses membership values as enriched numerical features for machine learning. Consequently, each input variable contributes multiple degrees of membership that provide richer information for classification. Thus, the fuzzy layer supports interpretability and uncertainty representation, while ELM learns class boundaries from data.

2.4 Extreme Learning Machine Model

The classifier was implemented using the Extreme Learning Machine (ELM), a single-hidden-layer feedforward neural network that provides fast learning by randomly assigning the input weights and hidden-layer biases while analytically estimating the output weights. Let X denote the fuzzy feature matrix, W the randomly generated input weight matrix, b the hidden-layer bias vector, and $g(\cdot)$ the sigmoid activation function. The hidden-layer output matrix is computed as:

$$H = g(XW + b) \tag{1}$$

where H is the hidden-layer output matrix after applying the sigmoid activation function. The output weight matrix β was estimated analytically using ridge-regularized least squares as:

$$\beta = \left(\frac{I}{C} + H^T H\right)^{-1} H^T Y \tag{2}$$

where I is the identity matrix, C is the regularization parameter, and Y is the one-hot encoded target matrix. The final prediction was obtained by selecting the class corresponding to the maximum output value:

$$\hat{y} = \arg\max(H\beta) \tag{3}$$

where $\hat{y}$ denotes the predicted crop class.

The ELM architecture consisted of 21 input neurons, 512 hidden neurons, and 22 output neurons. The input layer represents the fuzzy transformation of the seven agro-environmental variables into 21 membership features, while the output layer corresponds to the 22 crop classes. The hidden layer employed the sigmoid activation function to model nonlinear relationships between soil and climate conditions and crop suitability. A hidden-layer size of 512 neurons was selected to provide sufficient representation capability while maintaining efficient computation. Since ELM estimates the output weights analytically rather than through iterative backpropagation, the training process is computationally efficient and well suited for deployment in web-based decision-support systems requiring rapid prediction responses.

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Table 2. Dataset and Model Configuration

Component	Specification
Dataset	Crop Recommendation Dataset, 2,200 records
Input variables	N, P, K, temperature, humidity, pH, rainfall
Target classes	22 food and horticultural crop labels
Feature transformation	Triangular fuzzy membership: low, medium, high
Input dimension after fuzzification	21 features
Classifier	Extreme Learning Machine
Hidden layer	512 neurons
Activation and regularization	Sigmoid; ridge-regularized analytic learning

2.5 Web System Implementation and Evaluation

The trained model was deployed as a web-based decision support system using Flask, HTML/CSS, and MySQL. User inputs are normalized and fuzzified before being processed by the trained Fuzzy-ELM model, while prediction results are stored for future reference. The dashboard also supports BMKG weather integration to reflect current environmental conditions and maintain prediction history for agribusiness analysis.

The application consists of four modules: dashboard, crop prediction, crop information, and prediction history. These modules provide environmental summaries, crop recommendations, supporting crop information, and records of previous predictions to improve future decision-making. Deploying the model through a web interface enhances its accessibility and practical use, enabling future integration with advisory services and digital agriculture platforms. Model performance was evaluated using accuracy, precision, recall, and F1-score for multiclass classification [20], [21], [22]. The application was further validated through black-box testing and User Acceptance Testing (UAT) with five respondents using a five-point Likert scale.

3. Result and Discussion

3.1 Preprocessing and Fuzzy Representation Results

The preprocessing stage confirmed that all 2,200 observations were suitable for modelling. Min-max normalization standardized the input variables, while fuzzy transformation expanded the original seven variables into 21 membership-based features. Representing each variable as low, medium, and high membership degrees better captures gradual crop suitability than crisp thresholds, reflecting how soil and climate conditions are interpreted in agricultural practice.

The ELM model was trained using 21 input features, 512 hidden neurons, and 22 output classes. A large hidden layer and ridge regularization were employed to improve generalization and numerical stability. This configuration preserves the main advantage of ELM—fast analytic learning without iterative backpropagation while supporting multiclass classification [14], [15]. Since most computation occurs during training, the deployed web application can generate recommendations efficiently, making it suitable for agribusiness decision support.

3.2 Model Classification Performance

The classification performance of the proposed Fuzzy-ELM model was evaluated using accuracy, precision, recall, and F1-score, as summarized in Table 3. The model achieved an accuracy score of 0.95, indicating strong overall predictive performance. The macro-average precision and recall values were both 0.95, while the macro-average F1-score was 0.94. The close relationship between macro-average and weighted-average scores indicates that the model did not perform well only on dominant classes, but also maintained balanced recognition across the 22 crop classes. This is particularly important for crop recommendation because the practical cost of misclassification may differ across crops and locations.

Table 3. Evaluation Results of the Fuzzy-ELM Model

Metric	Result
Accuracy	0.95
Macro-average precision	0.95
Macro-average recall	0.95
Macro-average F1-score	0.94
Weighted-average precision	0.95
Weighted-average recall	0.95
Weighted-average F1-score	0.95

The confusion matrix shows a strong diagonal pattern, indicating that most crop classes were correctly predicted. A small number of misclassifications occurred among crops with similar agro-environmental

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characteristics, particularly where nutrient, pH, rainfall, or humidity requirements overlap. This suggests that fuzzy membership helps reduce rigid boundary problems, although it cannot fully eliminate class overlap in crop suitability data.

From an agribusiness perspective, the model should be treated as a decision-support tool rather than an autonomous decision-maker. The recommendation can provide a data-driven starting point, but users still need to consider market demand, seed availability, input costs, water access, labour capacity, and local cultivation knowledge. Therefore, the value of the system lies not only in predictive performance, but also in its usability as a web-based agribusiness application.
To further examine the distribution of correct and incorrect predictions across crop classes, the confusion matrix is presented in Figure 1.

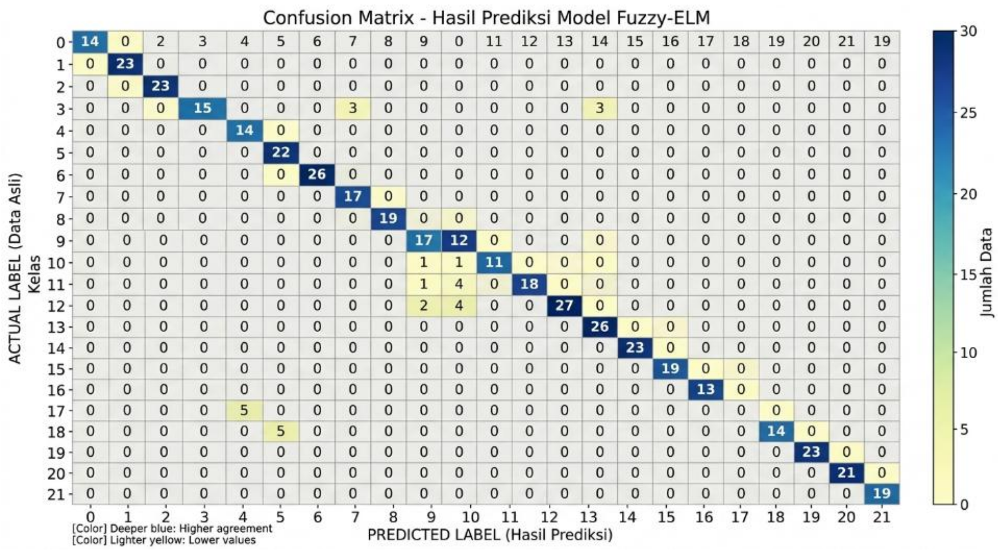

Figure 1. Confusion Matrix of the Fuzzy-ELM Crop Recommendation Model

3.3 Web Application Testing and User Acceptance

As presented in Table 4, the proposed system was successfully implemented as a web-based agribusiness decision-support application. Black-box testing confirmed that all 11 core functions operated correctly, including input validation, prediction, result display, data storage, and history access. User Acceptance Testing (UAT) achieved a score of 367/375 (97.86%), indicating very high user acceptance and confirming that the system is practical and easy to use.

The dashboard integrates environmental information, crop recommendations, and prediction history, while the prediction module enables users to input soil and climate parameters and receive recommendation results. Although respondents rated the system highly, the lower scores on colour/design and decision efficiency suggest that future work should focus on interface refinement and user guidance to further improve usability.

Table 4. System Testing and User Acceptance Results

Evaluation Aspect	Observed Result	Interpretation
Black-box testing	11 of 11 functions valid in three test rounds	Core system functions operated according to expected scenarios
UAT total score	367 of 375	Very high user acceptance
UAT percentage	97.86%	Very feasible for practical use
Slightly lower indicators	Colour/design and decision-efficiency items reached 92.00%	Minor improvement is needed in interface refinement and user guidance

3.4 SmartFarming Application Interface

Figures 2 and 3 present the implementation of the proposed SmartFarming application. Figure 3 shows the analytics dashboard, which summarizes system information, including crop recommendations, AI status, environmental conditions, commodity distribution, agricultural news, and prediction history. Figure 4 presents the crop recommendation interface, where users input soil parameters and receive crop recommendations along with basic cultivation tips to support crop selection.

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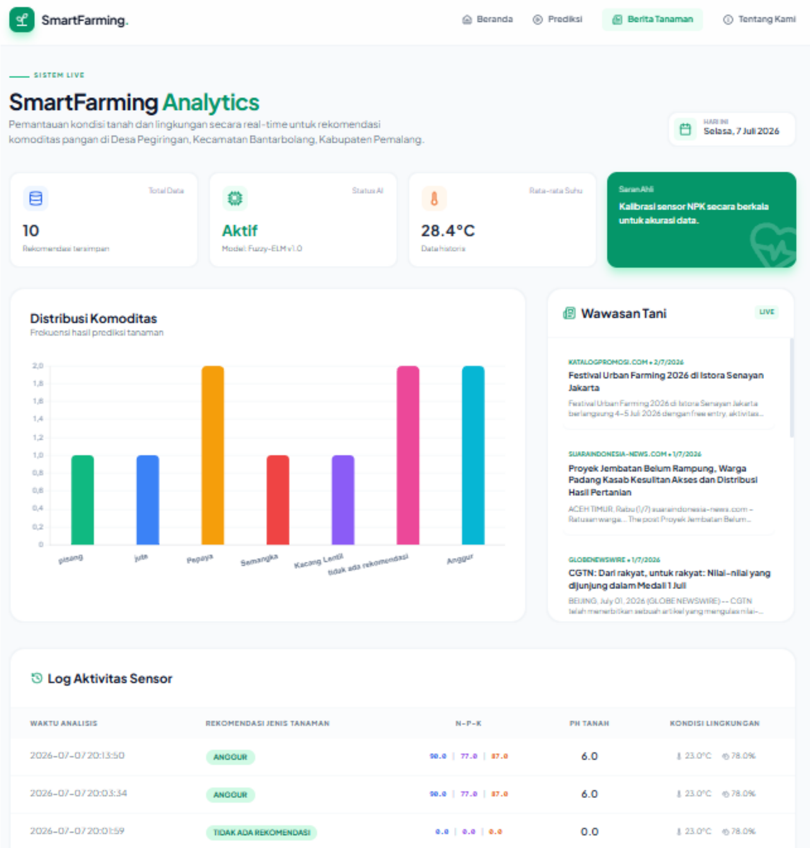

Figure 2. SmartFarming Analytics Dashboard

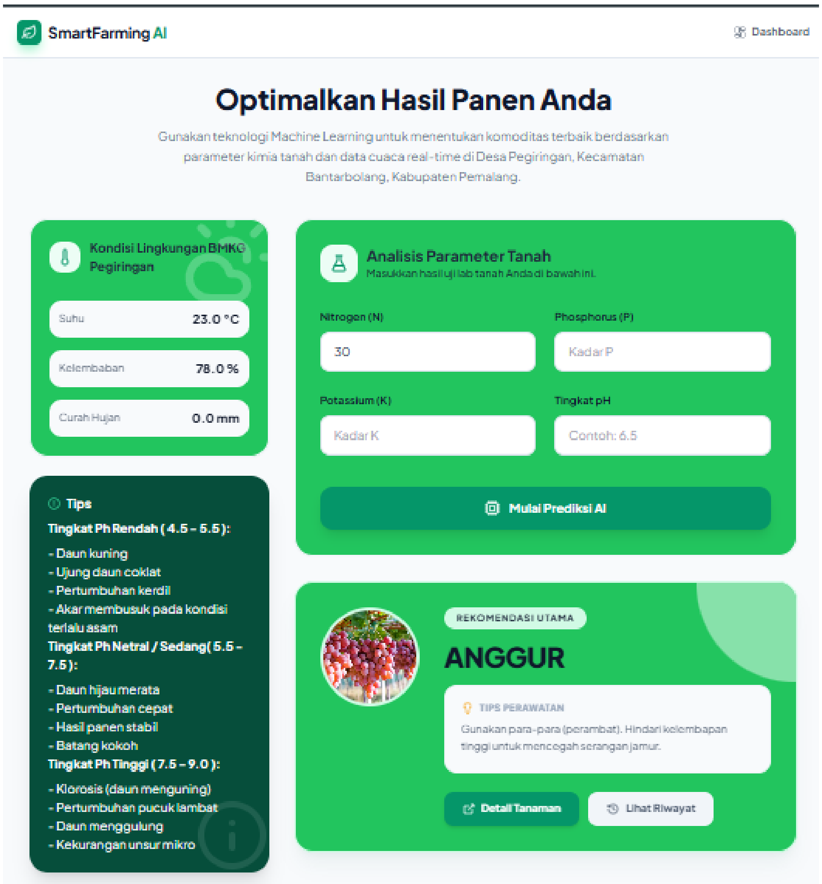

Figure 3. Crop Recommendation Interface

4. Conclusion

This study developed a web-based crop recommendation system for agribusiness decision support by integrating Fuzzy Logic and Extreme Learning Machine. Fuzzy Triangular Membership Functions transformed seven crisp agro-environmental variables into 21 linguistic membership features, while ELM performed multiclass classification across 22 crop labels. The proposed model achieved 95.00% accuracy, with macro-average precision of 0.95, recall of 0.95, and F1-score of 0.94. These results indicate that the hybrid model can classify crop suitability with strong and balanced performance.

The system implementation using Flask, MySQL, and a web dashboard showed that the model can be operationalized as a practical decision-support tool for digital agribusiness. Black-box testing achieved 100% functional validity, and UAT produced a feasibility score of 97.86%. These results show that the proposed system is not only algorithmically feasible, but also acceptable as an application interface for users who need practical crop-selection support. The main contribution of this study is the integration of fuzzy feature representation, fast ELM classification, and web-based implementation into one agribusiness-oriented application. The fuzzy layer helps represent uncertainty in soil and climate variables, ELM provides efficient multiclass classification, and the web application converts the model into an accessible decision-support tool. This combination strengthens the applied intelligence value of the study because it connects computational modelling with operational agribusiness use.

Future research should integrate IoT soil sensors, use field data from local agricultural contexts, optimize ELM parameters dynamically, include economic variables such as input costs and expected prices, and improve user-facing explanations of recommendation results. Further validation with larger farmer and agribusiness-user samples is also necessary to assess adoption, trust, and practical usefulness in real production environments.

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