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Enhanced Millet Crop Yield Prediction Using an Optimized Hybrid Fuzzy Logic Model

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Abstract

Accurate crop prediction is crucial for optimizing agricultural operations and ensuring food security. Because existing techniques do not consider the intricate interconnections between many environmental factors, predicting crop growth using these approaches is difficult. Some have proposed using fuzzy logic to solve this issue. Fuzzy models have gained fame in fields such as security-related research due to their interpretability. Though they aren't always accurate, expert-based fuzzy models are simple to understand. Although numerically-based fuzzy models are more precise, they are also more difficult to understand and work with. This study presents a hybrid approach to crop prediction using a Fuzzy Network (FN) and the Fuzzy C-Means clustering method. Building a Mamdani rule-based framework, the model employs an expert system approach and the data-driven FCM methodology. The FN technique combines these two approaches to boost performance. To get even better results with the fuzzy set parameters, we use the Crayfish Optimization Algorithm (COA). The performance of the proposed model may be evaluated by comparing it to the standard FCM technique on different datasets. The findings show that our model outperforms others in crop prediction and is more accurate, transparent, and interpretable.

Keywords: Millet Crop, Prediction, Optimization, Hybrid Model, FCM.

1 Introduction

The agricultural sector is vital to many countries because it provides a steady income for many people, provides food, and employs a large number of people (Sugandh et al., 2023; Zhong et al., 2019). The coarse grains known as millet are rich in several nutrients, including protein, fiber, vitamins, and minerals. Millets are gluten-free and packed with nutrients. Many types of millets exist, including jowar, ragi, foxtail millet, bajra, and many more. Plant growth monitoring is an essential part of modern precision farming to provide food security and sustainability by helping farmers make the most efficient use of their resources and produce crops of the highest possible quality and yield. The complex relationship between a plant's genotypes and its environment leads to the plant's development. Plantation

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managers need in-depth knowledge of individual plants to help with decisions about early pest and disease prevention, harvesting, and fertilization (Feifei, 2024).

The more standard methods of agricultural yield prediction sometimes include the examination of previous records and statistical tools (Dharmaraja et al., 2020). The complicated and nonlinear interactions seen in agricultural systems are often disregarded by these methods, despite their usefulness in understanding the dynamics of crop production (Elavarasan & Vincent, 2020b). First and foremost, they may not take into consideration how changing environmental conditions affect agricultural yields (dos Santos Ferreira et al., 2019). Machine learning and fuzzy logic modeling are two more sophisticated approaches that researchers have used to avoid these limitations. Fuzzy logic provides a realistic basis for simulating the uncertainties inherent in agricultural systems; it is an AI method based on the way humans make judgments when given confusing or incorrect information (Pandey et al., 2008). Unlike conventional binary logic, which depends on black-and-white distinctions between true and false, fuzzy logic permits the representation of fuzzy and imprecise ideas via the use of language variables and fuzzy sets. Fuzzy logic may be used by researchers to improve the accuracy and reliability of systems that estimate agricultural yields. This might lead to a better representation of the complexities and inherent uncertainties in agricultural systems.

The use of fuzzy logic modeling approaches in this study improves upon previous efforts by providing a more accurate, reliable, and context-aware method of predicting millet crop yields. Our approach offers a hybrid solution by combining the prediction power of a Fuzzy Network (FN) with the clustering capability of the Fuzzy C-Means (FCM) algorithm. Locating the Mamdani rule-based model structure is achieved by combining the data-based FCM algorithm with the expert-system technique, which depends on expert knowledge. Both of these procedures are part of the FN method. Optimizing the fuzzy set's parameters is possible with the help of the Crayfish Optimization Algorithm (COA) (Veerasamy & Fredrik, 2023).

2 Literature Survey

Several researchers, including, Adesh (Patankar & Kapoor, 2024), Askar (Choudhury & Jones, 2014), Sachin (Suvarna & Bharadwaj, 2024; Kumar & Kumar, 2015), Vikas (Lamba & Dhaka, 2014), Narendra (Kapoor & Iyer, 2024), and Pankaj (Kumar, 2011), have explored several methods for estimating agricultural yields, including fuzzy models and artificial neural networks. Sachin showed that fuzzy approaches are important for agricultural forecasting by studying how to use fuzzy time series models to predict rice production. The pearl millet crop ('bajra') was the subject of an empirical study by Dharmaraja et al. (2020) that aimed to forecast agricultural production using appropriate statistical models, including regression and time-series models (You et al., 2017). Additionally, prediction models that use an exogenous variable, including ARIMA and ARIMAX, have been used. The ARIMAX model had superior results for 'bajra' when compared to the regression time series model (Elavarasan & Vincent, 2020a; Verma & Reddy, 2025)

Precision farming systems that utilize deep learning to identify and discriminate between different types of weeds have the potential to increase crop yields. Robotic weed recognition systems for grasslands based on deep learning were proposed by Kounalakis et al., (2019). Furthermore, Ferreira et al (Khaki & Wang, 2019) used unsupervised deep learning to present a strategy for semi-automatic data labelling in weed discrimination. Deep learning approaches provide new points of view for plant disease detection, which is crucial for sustainable agriculture (Tan et al., 2024; Kounalakis et al., 2019; Khaki et al., 2020).

Khaki et al., (Verma & Reddy, 2025) accurately predicted corn productivity and yield differences across corn hybrids using machine learning. You et al (Kumar et al., 2010; Lee et al., 2020) estimated soybean yield from remotely sensed data collected before the crop using DL algorithms. Furthermore, an artificial neural network (ANN) model was created to forecast the consequences on the Iranian ecology and the plantations of black, green, and oolong teas (Akrami et al., 2024). A convolutional neural network (CNN) and a recurrent neural network (RNN) performed better when combined to forecast corn and soybean yields, according to LASSO and RF's comparison of deep fully connected neural networks' performance (Khanali et al., 2017). A decision-support system was created by researchers using environmental and soil data (Sharma & Iyer, 2023; Kumar & Kumar, 2012).

While deep learning has helped in crop development, more robustness improvements and faster, more accurate learning frameworks are needed. To meet these needs, we offer a new method called a fuzzy network (FN) that integrates fuzzy systems with fuzzy C-Means. Optimal performance of the fuzzy set parameters is achieved by utilizing a Crayfish Optimization Algorithm (COA). The ever-changing demands of agricultural systems can be enhanced with the use of FN, a powerful tool for representing dynamic input-output characteristics.

3 Proposed System

To accurately forecast millet harvest production, our study methodology incorporates a Fuzzy Network (FN) approach with the Fuzzy C-Means (FCM) clustering algorithm. Best values for the fuzzy set parameters are obtained by applying the Crayfish Optimization Algorithm (COA).

Our methodology begins with gathering appropriate information on weather conditions (temperature, precipitation, humidity), soil properties (moisture content, pH, nutrient levels), agricultural management practices (irrigation, fertilization), and past yield records, among other factors that affect millet crop yield. All of our predictive modelling depends on this data. Figure 1 represents the block diagram of proposed system.

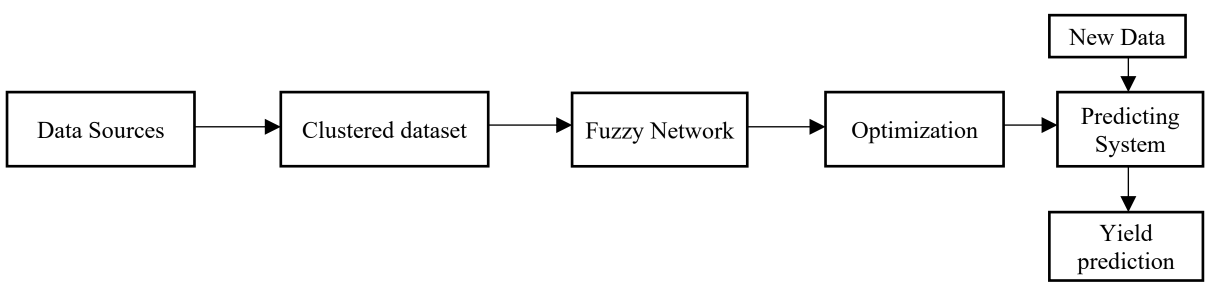

Figure 1: Block Diagram of Proposed Model

After that, we use the input characteristics' similarities to divide the gathered data into separate clusters using the Fuzzy C-Means technique. We hope to find trends and underlying structures in the dataset that might affect the variability of millet crop yields by grouping together data points that are comparable. The underlying features of various locations or farming practices can be better understood by first finding homogeneous groups of data points.

3.1 Fuzzy C Mean Clustering

Fuzzy c-means is a variant of the k-means partitional method that incorporates fuzzy logic. Figure 2 demonstrates the fuzzy c-means algorithm flow diagram. To find the centroid (or prototype) of a cluster, fuzzy c-means takes the average of all samples and adjusts it for their degree (uk) of cluster membership (Ck):

$$center_k = \frac{\sum_t u_k^m t - t}{\sum_t u_k t} \qquad (11)$$

The inverse of the distance to the cluster center determines the degree of membership in a particular cluster:

$$u_k t \propto \frac{1}{d_{center_k,t}} \qquad (12)$$

The coefficients are normalized so that their sum equals one and fuzzified with a real parameter m > 1:

$$u_k t = \frac{1}{\sum_j \frac{dcenter_k, t}{dcenter_j, t}^{2/m-1}} \qquad (13)$$

Like linearly normalizing the coefficients such that, for m = 2, their sum is 1. When m is close to 1, the algorithm looks the most like k-means. A much larger weight is assigned to the cluster center that is closest to the example.

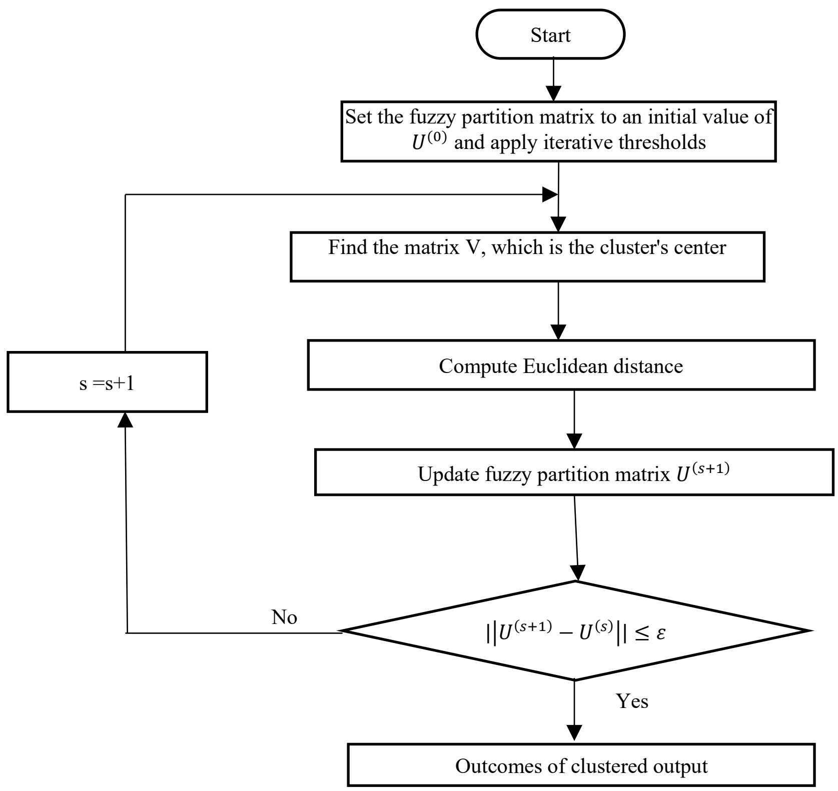

Figure 2: Flowchart of Fuzzy C Means Algorithm

Once the data is grouped, the next step is to establish a Fuzzy Network (FN). The FN approach simulates the relationship between the surroundings and crop yield through the construction of fuzzy conditional rules, using expert knowledge to organize according to Mamdani's rules. These guidelines are derived on knowledge to specific factors influence plant development, such as temperature and soil moisture. One such rule would be: "Crop yields will be high IF the temperature is high AND there is moderate rainfall." This is an ideal situation for Mamdani's fuzzy estimating approach. Due to the fact that it is essential for agricultural decision-making to be both interpretable and user-friendly.

Defuzzifying the fuzzy output (projected crop production) that results from merging a set of fuzzy inputs (derived from FCM clustering) is essential for improving the accuracy of predictions. The crayfish optimization algorithm (COA) was employed to optimize the fuzzy group's parameters, including the membership function and the weights rule.

3.2 Crayfish Optimization Algorithm (COA)

The Crayfish Optimization Algorithm was created by Jia et al. (Iqbal et al., 2015) by modelling crayfish behaviour. These include foraging, competition, and summer resorting. Temperature can be used to affect the foraging and competition behaviours, which mimic the optimization procedure's exploitation and exploration phases, respectively. Crayfish use caves as refuge during hot weather or as a place to fight for control of the cave. Crayfish use foraging behaviour as a form of exploration when the temperature is right. Increasing the temperature makes their pursuit of global answers more random. The COA procedure is explained in depth in the parts that follow.

3.2.1 Initialization

The COA randomly initiates the X^{th} population of N dim-dimensional potential solutions. Individual solution's position $X_{(i,j)}$ is represented by the following model:

$$X_{i,j} = Lb + (Ub + Lb) \times rand \qquad (1)$$

where (Ub) knows as the upper bound and (Lb) as lower bound of dimension j are defined.

Eq. (2) defines temperature, which is an important variable during the life cycle of crayfish. When summertime temperatures rise over 30 degrees, crayfish will seek refuge in colder waters. The crayfish begins its foraging behaviour when the weather is favourable. A temperature range of 15 to 30 degrees is defined as optimal foraging behaviour. Hence, a normal distribution, which is affected by temperature, can be used to reproduce the foraging behaviour. Equation (3) presents the mathematical description of this relationship.

$$temp = rand \times 15 + 20 \qquad (2)$$

$$p = C_1 \times \left(\frac{1}{\sqrt{2 \times \pi} \times \sigma} \times exp\right)\left(\frac{(temp - \mu)^2}{2\sigma^2}\right) \qquad (3)$$

where temp is the crayfish location's temperature and μ represents the ideal temperature for crayfish. C_1 and σ are also parameters that regulate the various crayfish temperatures.

3.2.2 Summer Resort Phase

The crayfish spends its summer vacation at cave X_{shade} if the temperature rises above 30 degrees during this stage, and this is defined as:

$$X_{shade} = X_{gbest} + X_{local} \qquad (4)$$

where X_{gbest} represents the optimally achieved location and X_{local} is the current population position. The crayfish typically engage in a random process of competition and fighting over the cave. On the reverse side, if rand is less than 0.5, then the crayfishes do not compete with each other and claim the cave for themselves.

$$X_{i,j}^{t+1} = X_{i,j}^{t} + C_2 \times rand \times (Xshade - X_i, j_t) \qquad (5)$$

$$C_2 = 2 - \left(\frac{t}{Max_{iter}}\right) \tag{6}$$

Max_{iter} expresses the maximum number of iterations, in which t represents the present iteration and (t+1) the upcoming updated crayfish location.

3.2.3 Competition Phase

This is the stage that the crayfish start fighting for dominion of the cave. A random number more than 0.5 and a temperature greater than 30 degrees indicate that there are additional crayfish in the cave. Accordingly, as shown in Eq. (7), they fight amongst themselves to gain control of the cave.

$$X_{i,j}^{t+1} = X_{i,j}^{t} - X_{z,j}^{t} + X_{shade} \tag{7}$$

$$z = round\big(rand \times (N-1)\big) + 1 \tag{8}$$

where N is the population's total agent count.

3.2.4 Foraging Phase

At this point, the crayfish have begun their search for food, which is the best course of action. Therefore, crayfish begin to search in various places when the temperature drops below 30 degrees. Here is the formula for the position and size of the food:

Essentially, it's a model of how to find the best answer to an issue.

$$X_{food} = X_G \tag{9}$$

$$Q = C_3 \times \left(\frac{fit_i}{fit_{food}}\right) \tag{10}$$

The COA algorithm takes inspiration from nature and mimics crayfish actions such as foraging, competing, and seeking shelter. The method uses temperature control to dynamically change the exploration and exploitation balance. Here, "search" means locating the optimal solution in the solution space, and "exploit" means making further improvements to that optimal solution. By modifying to better fit the observed data, COA helps optimize the fuzzy set parameters, which in turn guarantees that the fuzzy rules and membership functions give the most accurate estimates of crop yields.

Algorithm 1. Millet Crop Yield prediction using Fuzzy C means clustering.

Input: Dataset

Output: Optimized output

1) Initialize U= $[u_{ij}]$ matrix,$U^{(0)}$

2) Update the Membership Matrix $U^{(k)}$

$$u_{i\,j} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}}$$

Update the Cluster Centers C_j^k:

$$C_j^k = \frac{\sum_{i=1}^{N} u_{i\,j}^{(k)m} x_i}{\sum_{i=1}^{N} u_{i\,j}^{(k)m}}$$

3) For each Crayfish k:

$$J\left(U^{(k)}, C^{(k)}\right) = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{i\,j}^{(k)m} \,|\left|x_i - C_j^{(k)}\right||^2$$

4) If $||U^{(k=1)} - U^{(k)}|| < \varepsilon$

Else

return to step 2

Finally, we compare the hybrid model's performance to that of the traditional FCM method. When the model is tested on various datasets, its performance is evaluated using a number of parameters, such as precision, accuracy, and interpretability. The outcomes show that the proposed hybrid model outperforms the traditional FCM approach in all three domains. This model integrates data-driven clustering, expert-driven fuzzy rules, and COA optimization. The hybrid model is more trustworthy for predicting crop yield and has greater transparency, making it a better option for farmers and agricultural decision-makers who need accurate predictions.

4 Results and Discussion

4.1 Method Evaluation

The outcome is determined by evaluating the proposed model performance. The precision of the outcome is determined by applying particular formulas. These equations are as follows:

$$Precision = TP\,/\,(TP + FP)$$

$$Recall = TP\,/\,(TP + FN)$$

$$Accuracy = (TN + TP)\,/\,(TP + FP + TN + FN)$$

where TP represents the number of cases that are expected to be positive but actually provide positive results. False positives happen when things that were supposed to be good really end up being negative. TN happens when results for cases that were expected to be negative are really negative. A positive outcome from an expected negative event is known as FN.

4.2 Result Analysis

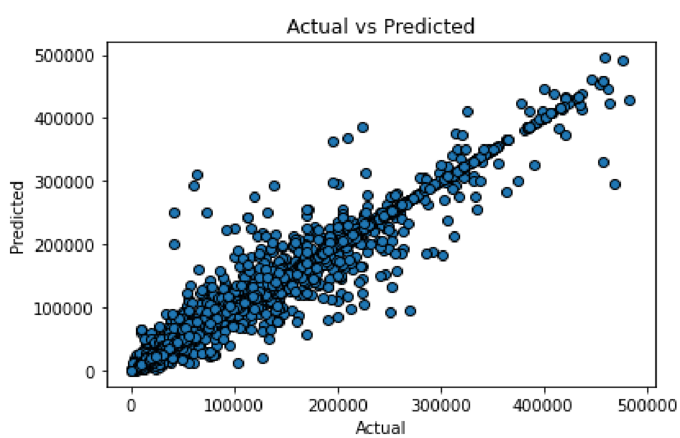

Figure 3: The Relation Between Actual vs Predicted Value

To assess the accuracy and effectiveness of a predictive model, it is essential to comprehend the connection between the actual values (ground truth) and the expected values (model outputs) in data analysis and predictive modelling (Figure 3). By comparing these numbers, we can see how well the model has picked up on the data's hidden patterns. There is a strong correlation between the proposed model's accuracy in predicting crop yields and the small discrepancy between actual and expected yields. The fact that there is only a little difference between the two numbers indicates that the model correctly predicts the data by identifying and describing the relationships and patterns present. This small dispersion demonstrates proposed models' resilient and useful it could be for predicting actual agricultural yields.

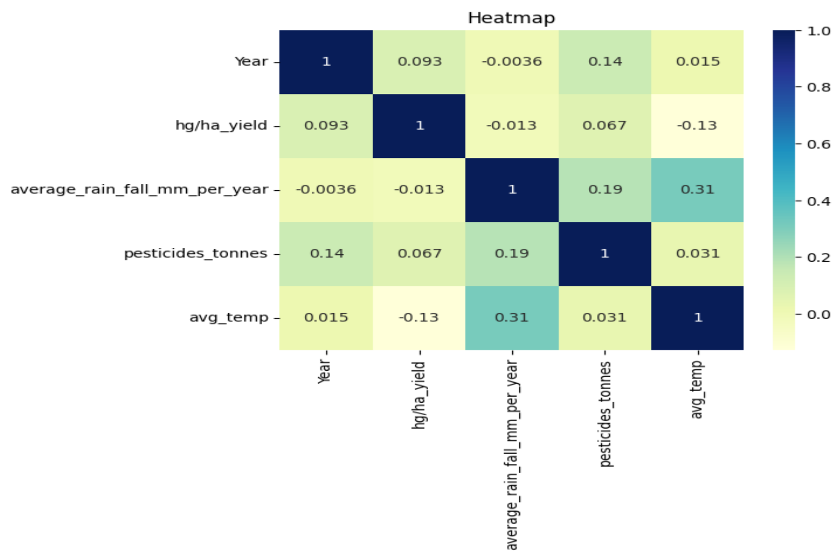

Figure 4: Heatmap for the Various Attribute Towards Yield Prediction

The target variable in this proposed model is the prediction of crop production, and a heatmap is a great visual tool for representing the connection between various variables and their relationship to that variable. To better understand which environmental variables, soil quality, weather data, etc., have the most impact on yield outcomes, the heatmap displays the correlation matrix of several parameters involved in crop yield prediction form Figure 4.

4.3 Comparative Performance Analysis

This section provides a brief overview of several innovative approaches that have been employed in previous publications (Jia et al., 2023; Layona et al., 2016). Despite being based on important performance parameters, the concept is contrasted with other identification algorithms and techniques. This hybrid FCM with FN-COA was chosen as the crop selection approach since it was more successful than other current methods. Figure 5 shows a compilation of graphical values derived from the output of the proposed decision-making model. The optimal performance is attained by using the recommended classifier model.

Table 1: Performance Analysis

Parameters	**Backpropagation**	**Backpropagation + CSO**	**Backpropagation +PSO**	**Hybrid FCM with FN-COA**
Recall	44%	63%	63%	95%
Precision	64%	83%	83%	98%
Accuracy	42%	67%	67%	98%

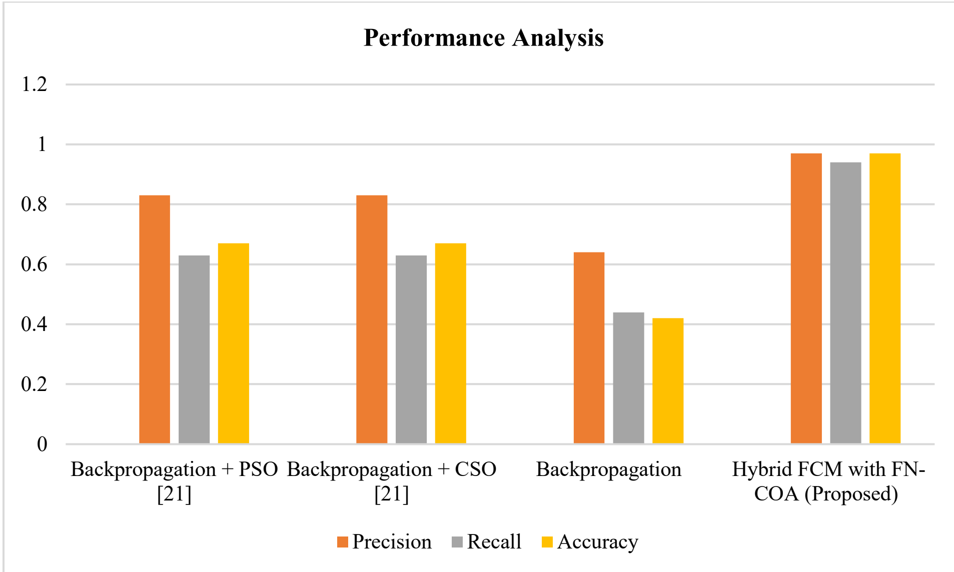

Figure 5: Evaluation of Existing and Proposed Methods in Comparison.

The results indicate that the proposed approach performs better. With a 95% recall, this performance showed 98% accuracy and 98% precision. Figure 3 and Table 1 show the overall effectiveness of the proposed model.

5 Conclusion

One of the hardest departments to integrate analytical findings is agriculture. Crop diseases, insect infestations, weather, and soil all have an impact on precision farming and crop yields. Our research concludes that a model for predicting millet crop yields using a combination of Fuzzy Logic and Fuzzy C-Means is an excellent tool. A Mamdani rule-based structure is generated using the expert-system technique, and the FCM algorithm is used for clustering; this model achieves a balance between accuracy and interpretability. To enhance performance, fuzzy set parameters are optimized using the Crayfish Optimization Algorithm (COA). When compared to more conventional approaches, the suggested model provides a more trustworthy and understandable answer to the problem of millet crop production, as well as better prediction accuracy and transparency.

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