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AN ENRICHED MULTI-GOAL EVOLUTIONARY ALGORITHM AND INTUITIONISTIC FUZZY COGNITIVE MAPS FOR PREDICTION OF CROP YIELD

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ABSTRACT

In India, agriculture is considered to be a prime activity for the most of populations. Therefore, an economic growth a nation mainly depends on the development of agricultural activities like improving crop production, utilizing developed technologies to monitor crop yield, etc. As a result, different crop yield monitoring systems have been developed to enhance the agricultural productivity. Among different systems, multi-objective firefly Optimized Fuzzy Cognitive Map (OFCM) was proposed for predicting the Arachis Hypogaea (groundnut) yield by using both soil and weather factors. Here, multi-objective firefly was applied for learning FCM by optimizing the weight parameters utilized in FCM. However, the Pareto-front issue has occurred in the firefly algorithm due to consider the multiple objective functions. Hence in this article, crowding distance between fireflies is computed for choosing appropriate fireflies. Moreover, an Improved Optimized OFCM (IOFCM) is proposed in which a modified multi-objective firefly optimization is used to minimize the randomness and achieve the global optima by improving the movement of fireflies. Though it achieves better optimization, FCM has high sensitive while input data are missing resulting in prediction decision is made with incomplete information. As a result, a modification in FCM is proposed to improve the prediction performance more effectively. In this modification, the value of each node in the FCM is computed by considering the hesitancy function that increases the prediction accuracy even some input data are missed. This newly proposed algorithm is called an Improved Optimized Intuitionistic FCM (IOIFCM). Finally, the experimental results show that the effectiveness of the proposed IOIFCM based crop yield prediction compared to the other optimization algorithms.

Keywords: yield prediction, fuzzy cognitive map, firefly algorithm, multi-objective firefly optimization, intuitionistic FCM.

INTRODUCTION

In each country, agriculture plays a significant role in economic growth. For agricultural management, crop yield prediction is performed according to the combination of factors which are more essential while specific monitoring condition is considered (Papageorgiou *et al.*, 2011). Over the past decades, numerous approaches such as crop models, data mining algorithms, statistical tools, etc., were developed for predicting the crop yield. Generally, data mining techniques have been utilized in decision-making process related to the agricultural activities which contain the large number of datasets like plant data, soil data, weather data, etc. Based on such approaches, yield improvement is achieved which impacts on agricultural productivity.

Among such approaches, FCM learning method (Papageorgiou *et al*., 2013) was proposed for yield prediction since it has different features like effortlessness, flexibility and the competence of approximating abstractive structures. However, the efficiency of this method was affected by inaccurate initial estimation of the weight values which also lead to undesired states of the system. Therefore in previous researches, FCM with Multi-Objective Firefly Algorithm (MFA) was proposed (Malarkodi and Arthi, 2017) to optimize the weight parameters of FCM and obtain the required steady states. This algorithm was used for yield prediction in groundnut using both soil and weather features such as wind, soil temperature, air temperature, humidity, pH, soil texture, Organic Matter (OM), etc. In this algorithm, the FCM weight parameters are learned and updated at each iteration by using MFA to predict the yield. But in MFA, the Pareto-front issue is not solved that causes selection of suitable fireflies for consecutive iterations.

herefore in this article, crowding distance is computed between fireflies to solve the Pareto-front issue. In addition, an IOFCM is proposed which uses a modified MFA for improving the performance of fireflies. In this algorithm, the randomness parameter used in MFA is modified to improve the convergence and movement updating for each iteration is also modified to obtain the global optima effectively. Even if, the performance of FCM is caused by missing some input data. For this reason, IOIFCM is proposed in which the value of each node in FCM is modified based on the hesitancy function. Though some input data are missing, this algorithm improves the prediction accuracy efficiently.

LITERATURE SURVEY

Artificial Bee Colony (ABC) optimization algorithm was proposed (Yesil *et al.,* 2013) for FCM learning by solving uni-model and multi-model numerical optimization problems. However, the convergence rate was less and the computational cost was high when the population of solutions was increased. A novel integrated fuzzy approach (Manoharan and Thangavelu, 2018) was proposed for determining the influential factors and also ranking the factors associated with the cotton yield by

using fuzzy decision-making trial and evaluation laboratory. But, an advanced hybrid approach was required for further improving the FCM classification and achieving better prediction.

A sugarcane yield classification technique (Natarajan *et al.*, 2016) was proposed based on the hybrid method. However, the computation complexity was high. On the other hand, the scalability of this model was less. FCM was modeled with non-linear Hebbian learning algorithm (Kannappan *et al.*, 2011) for predicting autistic disorder whereas, the classification accuracy was less. The FCM evolutionary learning process was extended (Froelich and Papageorgiou, 2014) for predicting multivariate time-series. A fuzzy inference system (Jayaram and Marad, 2012) was proposed for crop yield prediction. But, every single concept must utilize optimized transformation function independently.

PROPOSED METHODOLOGY FOR GROUNDNUT YIELD PREDICTION

In this section, the proposed IOIFCM algorithm for groundnut yield prediction is briefly explained. Initially, both weather and soil parameters are collected and given as input to the FCM system. In FCM, those parameters are learned based on the weight values which are provided by experts. Here, the main objective is to determine the values of cause-effect relationships among the concepts i.e., the weight values of FCM are selected for producing the desired decision by minimizing boundary of the output concepts and maximizing the prediction accuracy.

Improved Optimized Fuzzy Cognitive Map (IOFCM) Algorithm

An FCM is a fuzzy directed graph with a fuzzy set on a universe of discourse E and defined as follows:

$$\tilde{s} = \{\langle x, \mu_{\tilde{s}}(x)\rangle | x \in E\} \quad (1)$$

Where, $\mu_{\tilde{s}}: E \rightarrow [0,1]$ is the membership degree of the element $x \in E$ to the set $\tilde{s} \subset E$ and for each element $x \in E$, $0 \leq \mu_{\tilde{s}}(x) \leq 1$. The fuzzy nodes are represented as fuzzy concepts within the agriculture domain that occur to some degree. For example, a crop yield can be a concept which can occur in "low" or "medium" or "high" degree. Consider $\{C_1, \dots, C_N\}$ is the concept of an FCM and $\{C_{out_1}, \dots, C_{out_m}\}, 1 \leq m \leq N$ is the output concept whereas N refers to the total number of concepts. Each concept node is represented by the state vector $s_i \in [0,1], i = 1, \dots, N$. Each interconnection between two concepts C_i and C_j has a weight $w_{ij} \in [0,1]$. Its directed edges denote the relations between the concepts using if-then rules. From each rule, the influence of C_j on C_i is inferred as a linguistic value represented by a fuzzy set $(\tilde{I}_n)_{ij}$, on $[-1,1]$, from $\tilde{I} = \{\tilde{I}_n\}, n = 1, \dots, g$. Once the FCM is built, it can receive the data from its input concepts, perform reasoning and obtain crop yield decisions as values of its output concepts. The state is represented by a state vector s^t that consists of real node values $s_i^t \in [0,1], i = 1, \dots, N$ at iteration t. The value of each node is computed by,

$$s_i^{t+1} = f\left(s_i^t + \sum_{\substack{j=1 \\ j \neq i}}^{N} s_j^t \cdot w_{ji}\right) \quad (2)$$

Here, $f(\cdot)$ denotes the sigmoid function. The initial weight values are estimated by defuzzification of the concept influences. To select proper weight matrix $W = [w_{ij}], i, j = 1, \dots, m$, the value of output concept nodes are limited in strict bounds as,

$$s_{out_i}^{min} \leq s_{out_i} \leq s_{out_i}^{max}, i = 1,2, \dots, m \quad (3)$$

The objective function for achieving steady state output concept nodes is defined as,

$$I_1 = f_1(x_i) = min\left(\sum_{i=1}^{m} H\left(s_{out_i}^{min} - s_{out_i}\right)\left|s_{out_i}^{min} - s_{out_i}\right| + \sum_{i=1}^{m} H\left(s_{out_i} - s_{out_i}^{max}\right)\left|s_{out_i}^{max} - s_{out_i}\right|\right) \quad (4)$$

For each iteration, the non-zero weights are updated as follows:

$$w_{ji}^{t+1} = \gamma \cdot w_{ji}^t + \eta s_i^t\left(s_j^t - sgn\left(w_{ji}^t\right) w_{ji}^t s_i^t\right) \quad (5)$$

Here, $sgn(\cdot)$ refers to the sign function. The selection of proper weight parameters γ and η may influence the output concepts of FCM. Normally, the interconnections among concepts are defined by using if-then rules that assume a fuzzy linguistic variable. Those fuzzy variables are easily defuzzified to predict the yield with high accuracy. As a result, the other objective function to improve FCM performance is defined as,

$$\mathrm{I}_2 = \mathrm{f}_2(\mathrm{x_i}) = \mathrm{Max(Prediction\ Accuracy)}, \mathrm{i} = 1, \dots, \mathrm{n} \quad (6)$$

To achieve the above two objective functions, MFA is proposed in which Pareto-front issue is resolved by computing crowding distance between fireflies. In MFA, two processes are performed such as initialization and search. During initialization, a set of fireflies are generated with weight parameters. In addition, it requires to define light intensities (objective functions) I for each firefly as,

$$I = I_0\, exp(-\delta r_{ab}^2) \quad (7)$$

Here, I_0 refers to the original intensity value and δ is the light absorption coefficient. In addition, the attractiveness of fireflies x_a and x_b is defined as,

$$\beta = \beta_0\, exp(-\delta r_{ab}^2) \quad (8)$$

Here, β_0 refers to the attractiveness at $r_{ab} = 0$. The distance between two fireflies x_a and x_b is computed based on the Cartesian distance r_{ab}

$$r_{ab} = ||x_a - x_b|| = \sqrt{\sum_{n=1}^{d}(x_{a,n} - x_{b,n})^2} \quad (9)$$

In equation (9), $x_{a,n}$ refers n^{th} component of spatial coordinate x_a and $x_{b,n}$ refers n^{th} component of spatial coordinate x_b. If a movement of x_a which is attracted to x_b is updated as follows:

$$x_a^{t+1} = x_a^t + \beta \exp(-\delta r_{ab}^2)(x_b^t - x_a^t) + \alpha(\text{rand} - \tfrac{1}{2}) \quad (10)$$

In MFA, the above equation can be rewritten by adding objective functions for adjusting the search directions.

$$x_a^{t+1} = x_a^t + (I_{1_a}^t + I_{2_a}^t) \cdot \beta \exp(-\delta r_{ab}^2)(x_b^t - x_a^t) + \alpha(\text{rand} - \tfrac{1}{2}) \quad (11)$$

If no fireflies dominate x_a, it randomly moves to x_b position based on the step size L which is determined by weighing the difference between the upper and lower bounds of the decision space.

$$x_a^{t+1} = x_a^t + \alpha L \quad (12)$$

Moreover, the current position is together with the so far position for an efficient movement as,

$$x_a^{t+1} = P_s x_{gbest}^t + P_c x_a^t \quad (13)$$

Here, x_{gbest}^t is the global best so far, P_s and P_c are weights computed for so far position and current position based on the following equations,

$$P_s = \frac{I_{1a} - I_{gbest}}{I_{worst} - I_{gbest}} + \frac{I_{2a} - I_{gbest}}{I_{worst} - I_{gbest}} \quad (14)$$

$$P_c = \frac{I_{worst} - I_{1a}}{I_{worst} - I_{gbest}} + \frac{I_{worst} - I_{2a}}{I_{worst} - I_{gbest}} \quad (15)$$

According to the weight values, if the current position is near to the best so far solution, then the firefly has a high probability for moving around its current location. If the current location is far from the best so far, then the firefly has a high probability for moving towards the best so far solution. The current best x_a^t can be assigned either to minimum or maximum of a weighted sum of all the objective values defined as follows:

$$\psi(x_a) = \omega_1 f_1(x_a) + \omega_2 f_2(x_a) \quad (16)$$

Where ω_1 and ω_2 are the sequence of randomly generated numbers that are normalized resulting in $\omega_1 + \omega_2 = 1$. In the update stage, two functions are considered such as selecting the good fireflies for the next iteration and updating the members of the non-dominated set. For the next iteration, the crowding distance selection stage is used for selecting the members when the number of members in the candidate level is more than required. For firefly x_a, initially, firefly x_b is discovered $(b \neq a)$ that is nearest to x_a and then firefly x_c is found $(c \neq b \text{ and } c \neq a)$ that is nearest to but on the opposite side of x_a. This ensures that firefly x_b and firefly x_c, if it exists will be on the opposite side of firefly x_a, and their crowding distance (D_a) which is computed as follows:

$$D_a = d_{ab} + d_{ac} \quad (17)$$

In equation (17), d_{ab} denotes the distance between fireflies x_a and x_b. This algorithm always selects fireflies with higher values. Since, if a firefly with higher value means that the region has few other fireflies, then for maintaining the diversity of the solutions so that the region can be searched more thoroughly. If the size of the non-dominated set is predefined, then this update strategy is also used for maintaining the completeness of the non-dominated set. By computing the crowding distance between fireflies, the Pareto-front issue is solved. Moreover, convergence speed and movement of fireflies are required to improve the further performance of MFA algorithm.

Thus, a modified MFA is proposed to improve the movement of fireflies to achieve global optima and minimize the randomness by modifying the equations (9) & (11) can be rewritten as follows:

$$r_{a,gbest} = ||x_a - x_{gbest}|| = \sqrt{(x_a - x_{gbest})^2 + (y_b - y_{gbest})^2} \quad (18)$$

$$x_a^{t+1} = x_a^t + (I_{1_a}^t + I_{2_a}^t) \cdot \beta \exp(-\delta r_{a,gbest}^2)(x_{gbest}^t - x_a^t) + \alpha\left(rand - \tfrac{1}{2}\right) \quad (19)$$

In equation (19), the first term indicates the current position of x_a, the second term indicates the attractiveness and the third term denotes the randomization with α known as randomization parameter which is uniformly selected from the range of [0,1]. To achieve directed movement that directs random movement towards the global best, randomization parameter α can be represented as,

$$\alpha^* = \alpha_\infty + (\alpha_0 - \alpha_\infty)e^{-t} \quad (20)$$

In equation (20), α_0 refers initial value of α, α_∞ refers the final value of α and t ranges between $[0, t_{max}]$.

$$x_a^{t+1} = x_a^t + (I_{1_a}^t + I_{2_a}^t) \cdot \beta \exp(-\delta r_{a,gbest}^2)(x_{gbest}^t - x_a^t) + \alpha^*\left(rand - \tfrac{1}{2}\right) \quad (21)$$

Algorithm: IOFCM

Input: Number of nodes N in FCM, weight matrix W and Number of fireflies $\{x_1, x_2, \dots, x_n\}$ with weight parameters $(\gamma_1, \dots, \gamma_n)$ and $(\eta_1, \dots, \eta_n)$;

Output: Low yield, Medium yield or High yield

1. Define the first objective function $f_1(x_i)$ using (4);
2. Define the second objective function $f_2(x_i)$ using (6);
3. Define light absorption coefficient δ;
4. Initialize the population of fireflies $x_a, a = 1,2, \dots, N$ by constructing FCM with weight parameters;
5. Compute light intensity I or $f_1(x_i)$ and $f_2(x_i)$;
6. $While(t < t_{max})$
7. $For\ a = 1{:}n$
8. $For\ b = 1{:}n\ (b \neq a)$
9. $if(I_b > I_a)$
10. Vary attractiveness with distance r_{ab} via $exp(-\delta r_{ab})$;
11. Move firefly a towards b using (11);
12. Evaluate new solutions and update I or $f_1(x_i)$ and $f_2(x_i)$;
13. End if
14. End $For\ b$
15. if non-dominated solutions occur
16. $For\ c = 1{:}n\ (c \neq b\ and\ c \neq a)$
17. Find x_c that is nearest to but on the opposite side of x_a;
18. Compute the crowding distance, D_a using (17);
19. Update the movement of firefly x_{gbest} instead of x_a using (21);
20. End if
21. End $For\ c$
22. End $For\ a$
23. Sort fireflies and find the current best firefly (Best FCM);
24. End $While$
25. Use the obtained FCM during testing;
26. Predict the groundnut yield as low, medium or high;
27. End

Improved Optimized Intuitionistic Fuzzy Cognitive Map (IOIFCM) Algorithm

During the prediction process, FCM has high sensitivity to missing input data. As a result, IFCM is introduced for the prediction process that captures the degree of hesitancy in the relations defined by the experts between its concepts. This is proposed to weight the credibility of crisp or fuzzy rules with fuzzy certainty factors. IFS can be assumed as a generalized fuzzy set. Consider a universe of disclosure E, a fuzzy set can be defined as,

$$s = \{\langle x, \mu_s(x), \gamma_s(x)\rangle | x \in E\} \tag{22}$$

Here, $\mu_s: E \to [0,1]$ and $\gamma_s: E \to [0,1]$ are the membership and non-membership degree of the element $x \in E$ to the set $s \subset E$. For each element $x \in E$, it holds that $0 \leq \mu_s \leq 1, 0 \leq \gamma_s \leq 1$ and,

$$0 \leq \mu_s(x) + \gamma_s(x) \leq 1 \tag{23}$$

For each $x \in E$, if $\gamma_s(x) = 1 - \mu_s(x)$, s represents a fuzzy set. The following function represents the degree of the hesitancy of the element $x \in E$ to the set $s \in E$. According to the IFCM model, the cause-effect relations between two concepts C_i and $C_j, i, j = 1, \dots, N$ are defined by both their influence and degree of hesitates. The hesitancy is denoted by a fuzzy set $(\tilde{H}_n)_{ij}$, on [0,1], from $\tilde{H} = \{\tilde{H}_n\}, n = 1, \dots, h$. A subset is selected as,

$$\tilde{\Omega} \subseteq \tilde{I} \times \tilde{H} \tag{24}$$

Where

$$\tilde{I} \times \tilde{H} = \{(\tilde{I}_1, \tilde{H}_1), (\tilde{I}_1, \tilde{H}_2), \dots, (\tilde{I}_2, \tilde{H}_1), (\tilde{I}_2, \tilde{H}_2), \dots, (\tilde{I}_g, \tilde{H}_h)\} \tag{25}$$

In equation (24), $\tilde{I}$ refers the influence of concepts. A set Ω of IFS is built based on the following equation,

$$\tilde{\Omega} = \{\langle x, \mu_{\Omega_n}(x), \gamma_{\Omega_n}(x)\rangle | x \in [-1,1]\}, n = 1, \dots, w \leq m.p \tag{26}$$

In equation (26), $\mu_{\Omega_n}(x) = \mu_{\tilde{I}_m}(x), m = 1, \dots, g$ refers a membership function, $\gamma_{\Omega_n}(x) = 1 - \mu_{\tilde{I}_m}(x) - \mu_{\tilde{H}_p}(x), p = 1, \dots, h$ refers a non-membership function and $\pi_{\Omega_n}(x) = \mu_{\tilde{H}_p}(x)$ denotes the hesitancy function. Consider the hesitancy is consisting of a negative impact on the cause-effect relations among the concepts. Hence, the value of each node in each state vector $s_i^t \in [0,1], i = 1, \dots, N$ is represented as follows:

$$s_i^{t+1} = f\left(s_i^t + \sum_{\substack{j=1 \\ j \neq i}}^{N} s_j^t \cdot w_{ji}^{\mu} \cdot \left(1 - w_{ji}^{\pi}\right)\right) \tag{27}$$

Here, w_{ji} is the weight value of the edge directed from node j to node i, $w_{ji}^{\mu} \in [-1,1]$ and $w_{ji}^{\pi} \in [0,1]$ are influence weight and hesitancy weight related to the edge directed from node j to node i. Also, the weight factor $w_{ji}^{\mu} \cdot \left(1 - w_{ji}^{\pi}\right)$ preserves the sign of the influence and considers a zero value when two concepts are not related or the hesitancy weight is equal to unity. If the hesitancy value is zero, then the above equation (27) will depend only on the influence weight. Therefore, such weight values are chosen by modified MFA effectively and updated until the objective function is satisfied. Thus, the weight values of IFCM are selected to predict the groundnut yield more precisely.

RESULT AND DISCUSSIONS

In this section, the performance efficiency of IOIFCM is evaluated using Matlab and compared with the OFCM and IOFCM algorithms in terms of precision, recall, f-measure and accuracy. In this experiment, different datasets are used such as weather data and soil data. Weather data includes wind, humidity, temperature, etc., and soil data include soil texture, OM, pH, etc.

Precision

Precision is computed based on the prediction at true positive and false positive rates.

$$Precision = \frac{True\ positive}{True\ positive + False\ positive} \quad (28)$$

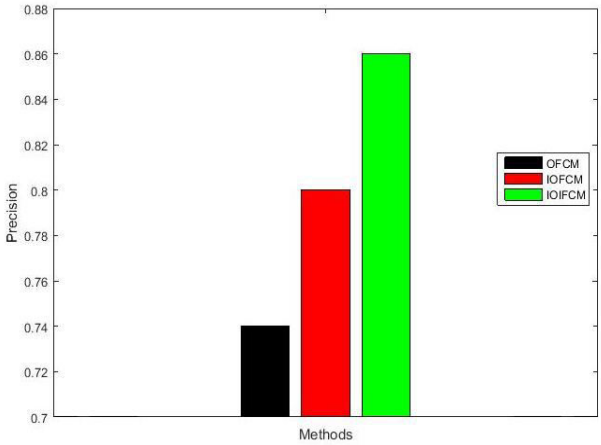

Figure-1. Comparison of precision.

Figure-1 shows the comparison of IOIFCM, IOFCM and OFCM in terms of precision. The precision of IOIFCM is 16.22% higher than OFCM and 8.11% higher than IOFCM method. From this analysis, it is observed that the proposed IOIFCM has better precision than the other algorithms.

Recall

Recall is computed based on the yield prediction at true positive and false negative rates.

$$Recall = \frac{Truepositive}{(Truepositive + Falsenegative)} \quad (29)$$

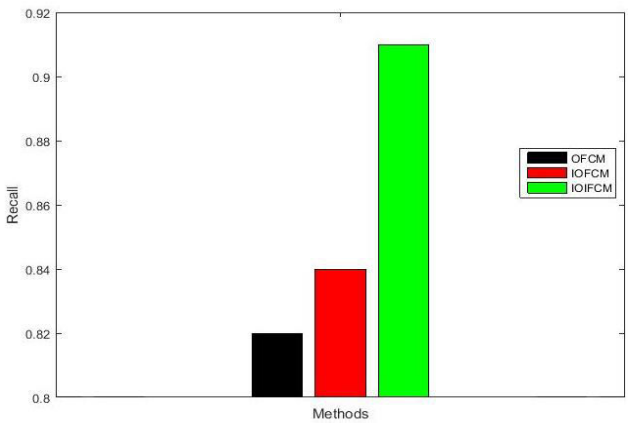

Figure-2. Comparison of recall.

Figure-2 shows the comparison of IOIFCM, IOFCM and OFCM in terms of recall. The recall of IOIFCM is 10.98% higher than OFCM and 8.33% higher than IOFCM method. From this analysis, it is observed that the proposed IOIFCM has better recall than the other algorithms.

F-measure

F-measure is computed by using both precision and recall as follows:

$$F - measure = 2 \times \left(\frac{precision \times recall}{precision + recall}\right) \quad (30)$$

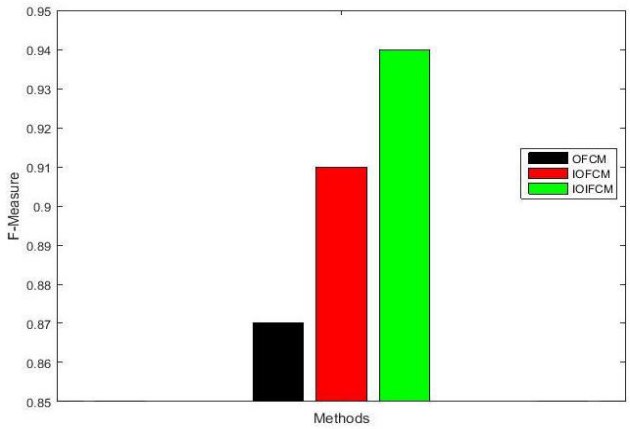

Figure-3. Comparison of F-Measure.

Figure-3 shows the comparison of IOIFCM, IOFCM and OFCM in terms of f-measure. The f-measure of IOIFCM is 8.05% higher than OFCM and 3.30% higher than IOFCM method. From this analysis, it is observed that the proposed IOIFCM has better f-measure than the other algorithms.

Accuracy

Accuracy is defined as the proportion of both true positives and true negatives among the total number of cases examined.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (31)$$

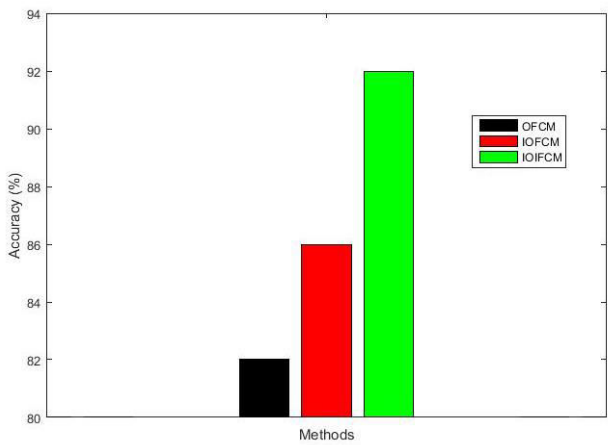

Figure-4. Comparison of accuracy.

Figure-4 shows the comparison of IOIFCM, IOFCM and OFCM in terms of accuracy. The accuracy of

IOIFCM is 12.20% higher than OFCM and 6.98% higher than IOFCM method. From this analysis, it is observed that the proposed IOIFCM has better accuracy than the other algorithms.

CONCLUSIONS

In this article, groundnut yield prediction is improved by using IOIFCM algorithm. Initially, the weather and soil characteristics are given as input to the FCM system. The weight values of FCM system should be chosen under the boundary constraint for maximizing the prediction accuracy. As a result, MFA is applied to select the most optimal weight parameters by solving the Pareto-front issue since it considers multiple objective functions. Moreover, modified MFA is proposed for minimizing randomness and improving the movement of fireflies towards global optima. In this algorithm, two objective functions are considered such as minimizing output concept boundary and maximizing prediction accuracy. Also, the degradation of prediction performance due to missing input data is overcome by IFCM algorithm. Finally, through the experimental results, it is proved that the proposed IOIFCM has better performance in terms of precision, recall, f-measure and accuracy than the other algorithms.

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