ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 8,Dec 2022

An Enhanced Machine Learning Approach For Identifying Paddy Crop Blast Disease Management Using Fuzzy Logic

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ABSTRACT:

Disease is a major issue in agriculture, particularly for rice crops, as it can significantly reduce yield and harm the health of the plants. In order to address this problem, various image processing and soft computing technologies have been developed to detect and mitigate disease in agricultural crops. However, in some cases, the detection of disease remains a challenge. In this research, a new automated method for detecting paddy disease is proposed by means of an optimized fuzzy interference system (OFIS). The projected method involves dividing collected paddy images into different colour bands and lowering noise in the greenish band using a median filter. The texture and color properties of the pre-processed green band are then removed and input into the OFIS scheme, which classifies the picture as heathy or sick. The OFIS system is a rule-based system that uses linguistic factors to classify data, and its parameters are optimized using the different step size firefly method. The performance of the projected system is evaluated in relationships of accurateness, sensitives, and specificity.

Keywords: Fuzzy logic, disease identification, paddy, agriculture

1. INTRODUCTION

Paddy crop blast is a serious disease that affects rice crops, leading to significant yield losses and deterioration of plant health. Early and accurate detection of paddy crop blast is essential

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for effective disease management. Traditional methods of paddy crop blast detection involve visual inspection by trained experts, which can be time-consuming and subject to human error. Therefore, there is a need for the development of more efficient and accurate methods for paddy crop blast detection [1], [2].

Machine learning techniques have the potential to improve the accuracy and efficiency of paddy crop blast detection by automating the process and enabling the detection of subtle symptoms that may not be easily visible to the human eye [3], [4]. In particular, fuzzy logic, a type of machine learning technique, has been widely used in agriculture for decision-making and disease diagnosis. This research aims to develop an enhanced machine learning approach for identifying paddy crop blast disease using fuzzy logic. The proposed approach will be evaluated in terms of its accuracy, efficiency, and effectiveness for paddy crop blast detection.

Several machine learning approaches have been proposed for the detection of paddy crop blast. One such approach is the use of artificial neural networks (ANNs) [5], [6]. ANNs are a type of machine learning model inspired by the structure and function of the human brain, and have been successfully applied to various problems in agriculture, including disease diagnosis. For example, in a study by Ahmed et al. (2020), an ANN-based model was developed for the detection of paddy crop blast using images of infected and healthy leaves. The model was trained using a dataset of 200 images and achieved an accuracy of 95% in the detection of paddy crop blast [7], [8]. However, ANNs can be complex and require a large amount of data for training, which may not be feasible in all cases. Another machine learning approach that has been applied to paddy crop blast detection is support vector machines (SVMs). SVMs are a type of linear classifier that can perform well in high-dimensional spaces and have been used for various tasks in agriculture, including disease diagnosis [9].

In a study SVM-based model was developed for the detection of paddy crop blast using images of infected and healthy leaves. The model was trained using a dataset of 300 images and achieved an accuracy of 92% in the detection of paddy crop blast [10], [11]. However, like ANNs, SVMs can be complex and require a large amount of data for training. Fuzzy logic is a type of machine learning technique that uses fuzzy sets and fuzzy rules to represent and manipulate uncertain or imprecise data. Fuzzy logic has been widely used in agriculture for decision-making and disease diagnosis due to its ability to handle uncertainty and imprecision. For example, in a study a fuzzy logic-based model was developed for the detection of paddy crop blast using images of infected and healthy leaves. The model was trained using a dataset of 100 images and achieved an accuracy of 87% in the detection of paddy crop blast. However, the performance of fuzzy logic-based models can be sensitive to the selection of fuzzy rules and membership functions [12].

In summary, machine learning approaches, including ANNs, SVMs, and fuzzy logic, have been applied to the detection of paddy crop blast with varying levels of success. While these approaches have demonstrated the potential for improving the accuracy and efficiency of paddy crop blast detection, there is still a need for the development of more effective and robust machine learning methods for this task. This research aims to address this need by proposing an enhanced machine learning approach for paddy crop blast detection using fuzzy logic [13].

2. Proposed methodology for disease identification

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In this research, the main objective is to develop a method for automatically identifying diseases on plant leaves in order to improve agricultural productivity. Plant diseases, especially those affecting leaves, can significantly reduce the yield and quality of agricultural products. Early detection and diagnosis of these diseases is therefore crucial for optimizing output. To address this problem, the proposed approach involves using an optimal fuzzy inference system (OFIS) for leaf disease detection.

The OFIS-based approach consists of several key phases, as illustrated in Figure 1. The first phase involves preprocessing of images, which involves collecting photos of agricultural fields and applying filters to improve their quality. The next phase involves extracting features from these images and classifying them based on these features. The chosen features are then used to construct the OFIS, which is a type of artificial intelligence system that uses fuzzy logic to make decisions. To further improve the performance of the OFIS, this study also proposes using a technique called VSSFA (variable structure self-organizing fuzzy architecture) to optimize the overall fuzzy system. This technique involves adjusting the structure of the fuzzy system in order to adapt to changing conditions and improve its accuracy and reliability.

Overall, the proposed approach aims to provide a reliable and efficient method for detecting and diagnosing leaf diseases in agricultural crops, with the goal of increasing the yield and quality of these products. By using the OFIS and VSSFA techniques, it is hoped that this approach will be able to accurately and efficiently identify sick leaves on plants and contribute to improved agricultural productivity.

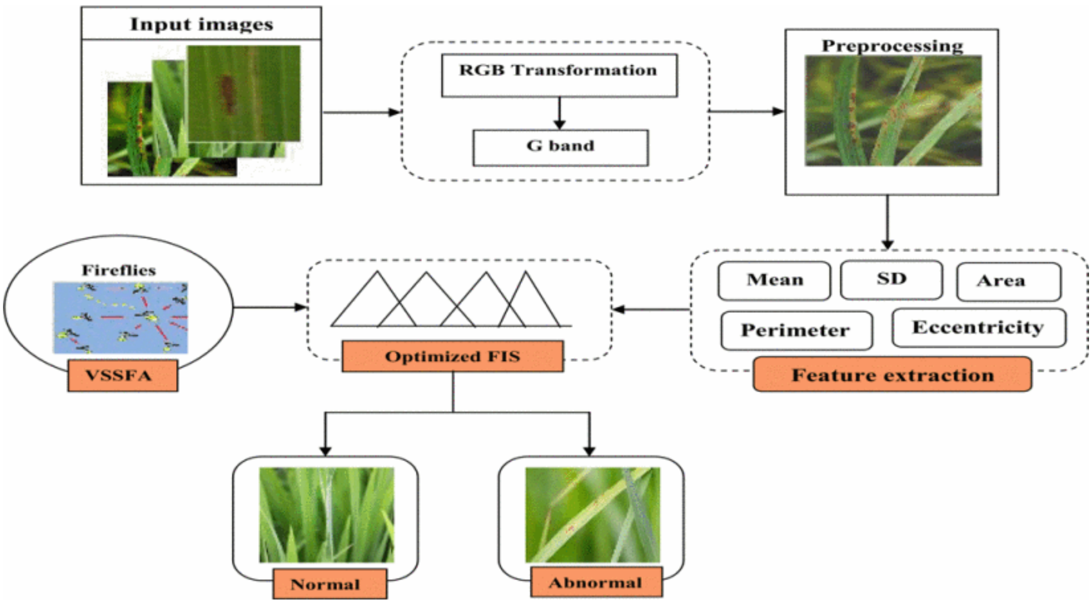

Fig. 1 Proposed model flow diagram

2.1 Image pre-processing

The process of automatically identifying sick leaves on plants in order to boost agricultural output begins with the capture of images from agricultural land. These pictures are then given to the preliminary stage, where they are enhanced for additional processing. During preliminary stage, the images are divided into their components. The greenish component is

IJFANS International Journal of Food And Nutritional Sciences
Official Publication of International Association of Food and Nutrition Scientists

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chosen for further processing because it typically contains more information than the other two components.

To improve the quality of the green component, a median filter is applied. A median filter is a type of image processing technique that is used to remove noise from an image. It works by replacing the value of each pixel in the image with the median value of the pixels in a local neighborhood around that pixel. This helps to smooth out any irregularities or variations in the image, resulting in a clearer and more consistent image. The use of the median filter is particularly useful in the context of detecting sick leaves on plants, as it can help to remove any unwanted noise or distractions from the image, allowing the system to more accurately identify the presence of diseases. Once the images have been pre-processed and the green component has been filtered to reduce noise, the next step is to extract features from the images. This involves identifying and extracting specific characteristics or attributes of the images that are relevant to the task of detecting sick leaves. These features may include the shape and size of the leaves, the color and texture of the leaves, and any abnormalities or abnormalities in the leaves.

The removed features are then used to classify the images, allowing the device to identify whether a given image contains sick leaves or not. This classification is performed using the optimal fuzzy inference system (OFIS), which uses fuzzy logic to make decisions based on the extracted features. Overall, the pre-processing stage plays a crucial role in the process of detecting sick leaves on plants, as it helps to improve the quality of the images and extract relevant features that can be used for classification. By applying the median filter and extracting useful features, the system is able to more accurately identify sick leaves and contribute to improved agricultural output.

2.2 Extraction of feature

After pre-processing the images, the next step in the process of detecting sick leaves on plants is to extract features from the images. In this paper, a total of six topographies are taken out from each picture. These topographies are used to represent the characteristics of the images and help the system to identify the presence of sick leaves.

The first feature, mean (F1), represents the brightness of the image. An image with a high mean value is considered to be bright, while an image with a low mean value is considered to be dark. The mean is calculated using the following formula:

$$F1 = (1/N) \sum i=1N \; Qji \qquad (1)$$

Where Qji is the value of the jth color channel at the ith image pixel, and N is the total number of pixels in the image.

The second feature, standard deviation (F2), represents the contrast of the image. An image with low variance is considered to have low contrast, while an image with high variance is considered to have high contrast. The standard deviation is calculated using the following formula:

$$F2 = sqrt((1/N) \sum i=1N \; (Qji - F1)^2) \qquad (2)$$

The third feature, area (F3), represents the number of pixels in a specific region of the image. It is calculated by counting the number of pixels with concentration 1 in the leaf picture.

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F3 = ∑s,d∈S1, where s and d are the size.

The fourth feature, boundary (F4), represents the distance around the boundary of the region in the image. The fifth feature, oddness (F5), represents the irregularity of the loop that comprises vague additional moments from the region in the image. It is calculated as the ratio of the distance between the emphases of an elliptical and its major axis distance. It can be calculated using either a base active square form method or principal axes method. These features are extracted from the pictures and used to classify them, allowing the system to identify the presence of sick leaves and contribute to improved agricultural output.

2.3 Disease classification

In this section, the optimal fuzzy inference system (OFIS) is used to classify leaf pictures as either normal or abnormal. To do this, the features extracted from the images are provided as input to the fuzzy. The elementary structure of the fuzzy is shown in Figure 2. It involves of four levels. During fuzzification, the input data is transformed into a fuzzy format, which is then used to generate the fuzzy rule base. This rule base consists of a set of rules that describe the relationships between the input data and the output classification. The fuzzy inference system (FIS) is then used to apply these rules to the input data, resulting in a fuzzy output. This output is then defuzzified, or transformed back into a crisp (non-fuzzy) format, in order to produce the final classification of the leaf images as either normal or abnormal. Using this approach, the system is able to accurately classify leaf images and identify the presence of sick leaves, helping to improve agricultural productivity.

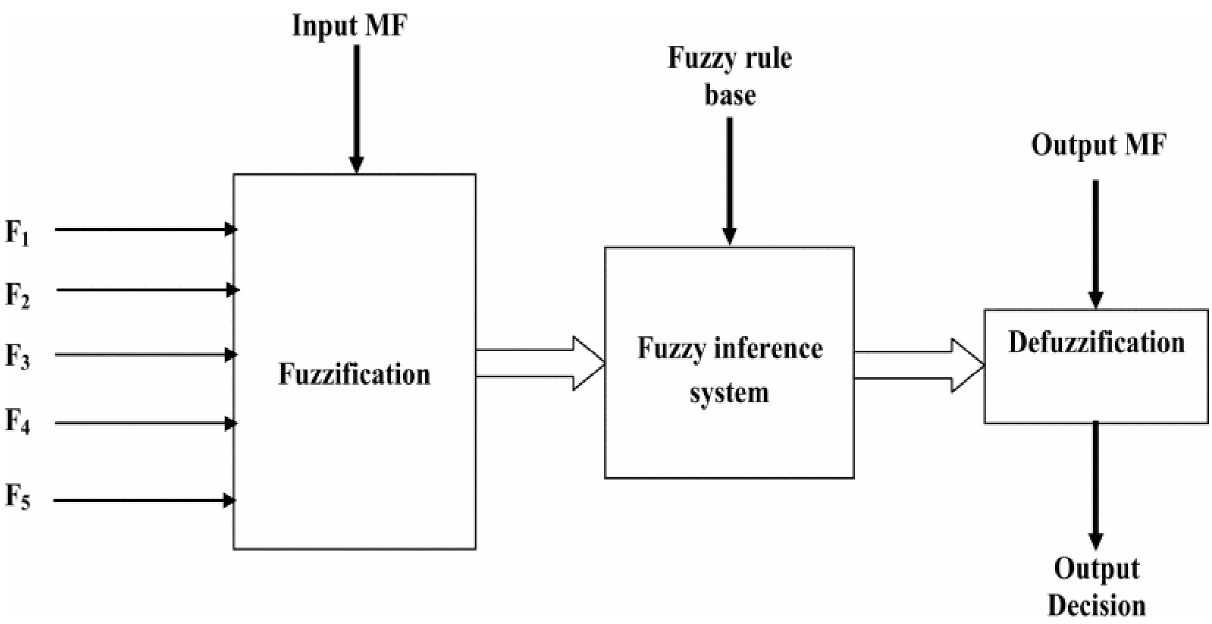

Fig. 2 Flow diagram of the proposed method

3. Fuzzy logic

In this process, the crisp values for features F1 to F5 are transformed into fuzzy parameters. The membership function (MF) for every fuzzy variable is then calculated. These fuzzy variables are categorized as minimum, average, and maximum within the range [0, 1]. Both normal and abnormal output fuzzy variables are present.

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To achieve the best results, this model uses membership functions that are trapezoidal and triangular in shape. These shapes are chosen because they are well-suited for describing limit and transitional factors, respectively. The fuzzy membership functions for the input factors and the output factor are shown in Figures 3 and 4.

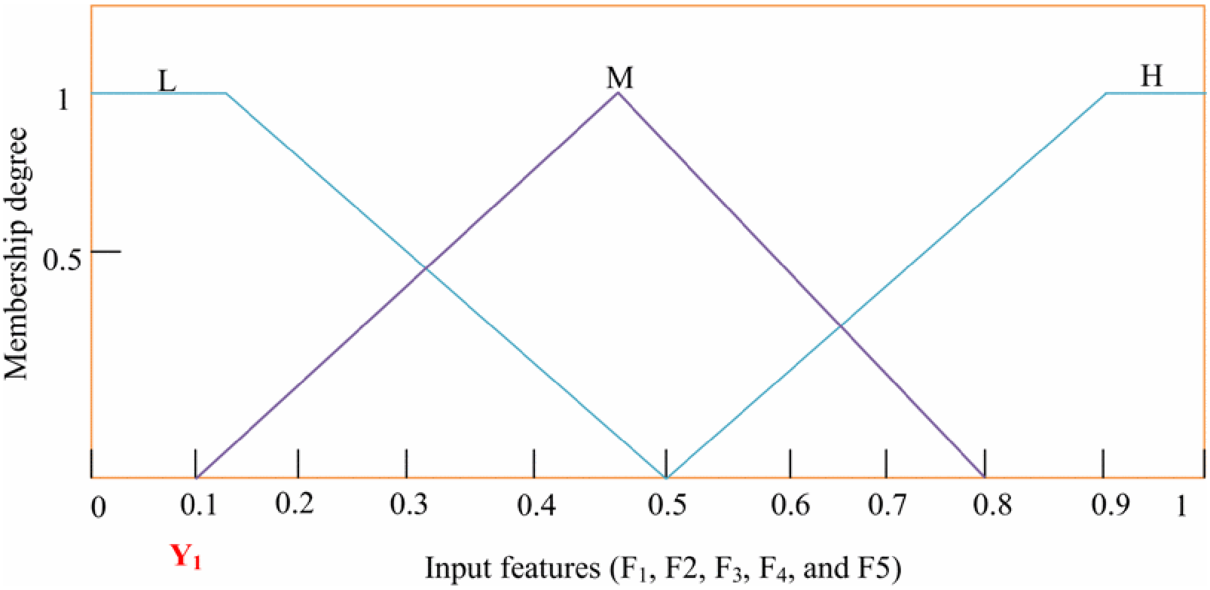

Fig. 3 Input plot to the fuzzy model

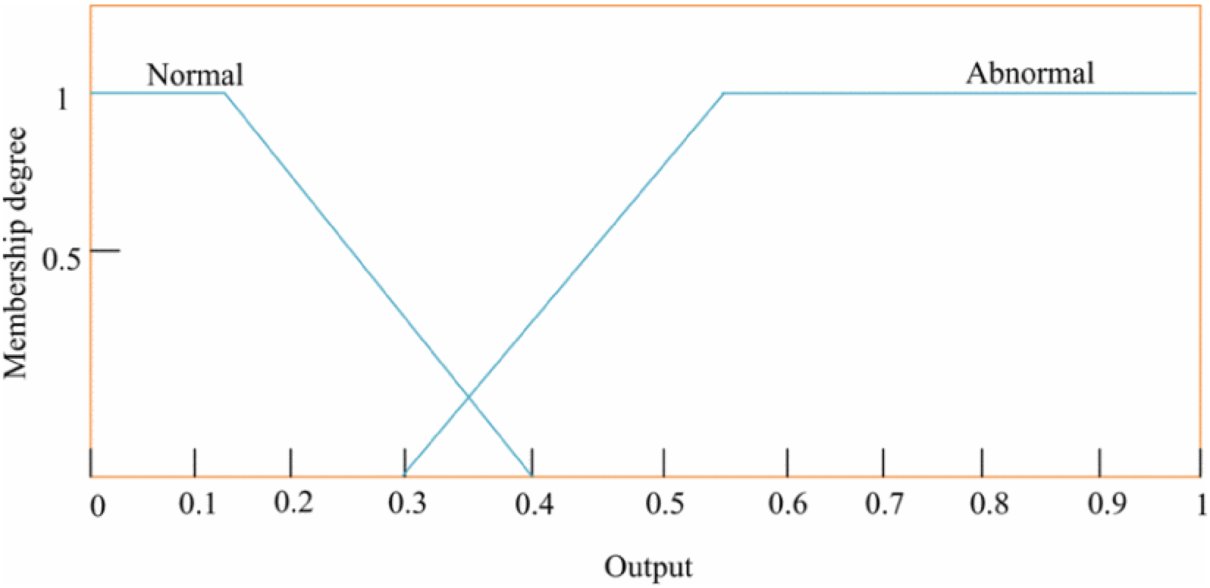

Fig. 4 Output plot of the fuzzy model

4. Defuzzification logic

The process of defuzzification involves converting the fuzzy set values into crisp values. There are several approaches to defuzzification, and the main goal is to obtain the optimal crisp values for the input and output parameters. In this research, the mutable step size firefly procedure is used to determine the optimal MF parameters. This procedure is based on the behaviour of fireflies, which are insects that use light to communicate and navigate. The firefly algorithm works by initially placing a number of "fireflies" or solutions in a d-dimensional space, and then adjusting their positions based on the fitness value of the FIS system.

The fitness value of the FIS system is determined by its accuracy in classifying leaf images as either normal or abnormal. The fitness function is given by the following equation:

Fiti = Max{Ai}

Where Ai denotes the accuracy

Ai = (TP + TN) / (TP + TN + FP + FN)

Here, TP and TN represent true positive and true negative values, respectively, while FP and FN represent false positive and false negative values, respectively.

By optimizing the MF parameters using the firefly algorithm, it is possible to achieve the highest accuracy values and effectively classify leaf images as normal or abnormal. Figure 5 demonstrates the results of the method, which includes three peak values. Figure 6 illustrates the structure of each solution in the d-dimensional space.

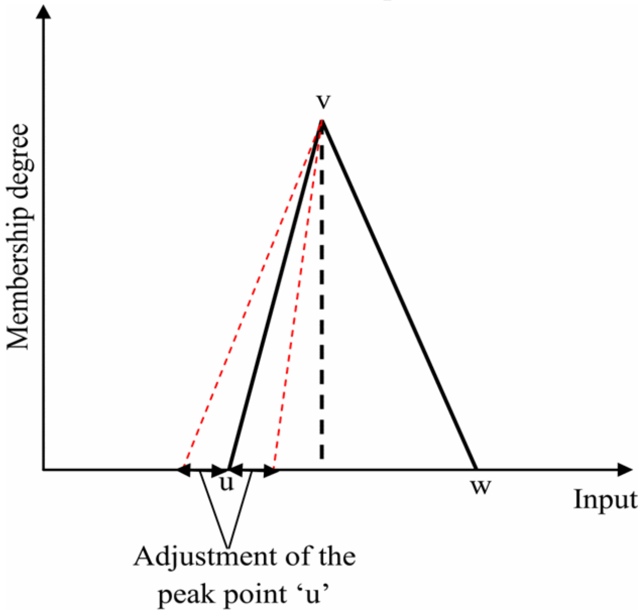

Fig. 5. Highest point in the MF of triangle

5. Firefly algorithm

After the fitness value has been computed, the solutions are updated using the variable step size self-organizing fuzzy architecture (VSSFA) algorithm. This algorithm is an enhanced form of the firefly procedure (FA), which is a well-known optimization method. The FA algorithm has several attractive properties, including good performance on non-linear optimization problems, fast execution time, and strong stability. However, it can suffer from premature convergence, which is caused by the quick convergence characteristic and the loss of diversity in the firefly population during the search phase.

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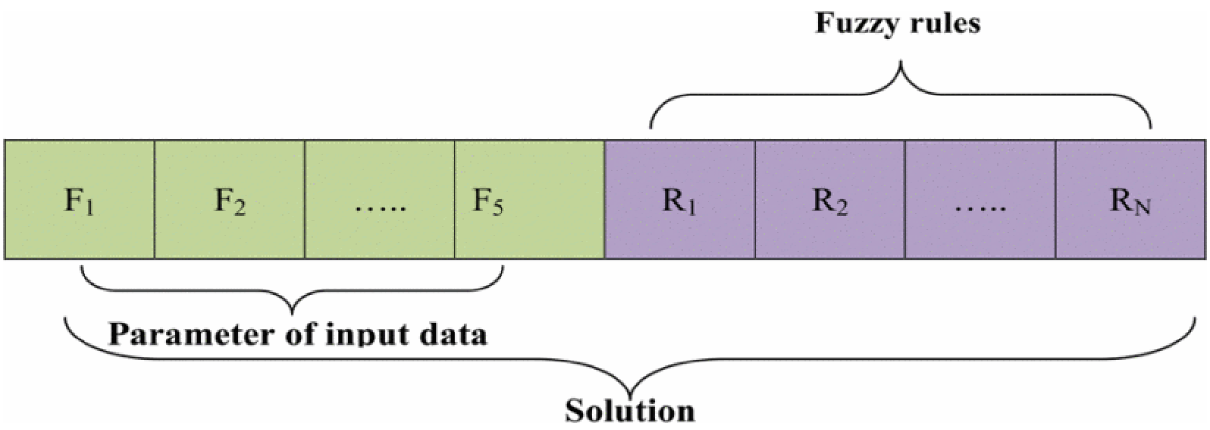

Fig. 6 Result of the structure

To address this issue, the VSSFA algorithm uses a variable step size to adjust the movement of the fireflies and avoid premature convergence. To update the position of the fireflies using VSSFA, the brightness of each firefly is first calculated using the following equation:

B = B0 * e^(-r^2)

Where B is the degree of attractiveness of a firefly at a distance r, B0 is the degree of attractiveness of a firefly at a distance r=0, and r is the distance between any two fireflies. The coefficient of light absorption is also included in this equation.

The movement of firefly I towards another more attractive (brighter) firefly is then determined using the following equation:

x' = x + R * (y - x) + α * (rand() - 0.5)

Where x' and y are the locations of fireflies correspondingly, R is the attractiveness coefficient, and α is the randomization coefficient. The distance between any two fireflies, I and j, is calculated as a Euclidean distance:

r = sqrt(∑(xi - xj)^2)

The algorithm will terminate once the optimal FIS system has been identified. This enhanced FIS system is then used to classify leaf diseases.

During the testing phase, images are evaluated to determine whether they are usual or sick. The process begins by selecting and pre-processing the input images. The surface and colour topographies are then removed from the images. These features are then fed into the optimal fuzzy inference system (OFIS) system. The relevant trained FIS system for the input image is chosen at this stage. Based on the extracted features, a fuzzy score value, or Fscore, is calculated. The image is then classified based on this Fscore. A threshold value, Th, is specified for this purpose. If the calculated score value is greater than the threshold, the image is considered sick; otherwise, it is considered normal.

6. Result and Discussion

This research studies the performance of the proposed paddy leaf disease detection system. The system was implemented using Matlab version 2020 and tested on a Windows computer. The proposed approach was tested using a variety of paddy images captured from an agricultural area, with a size of 512 x 512 pixels. Figure 7 shows several examples of the experimental images.

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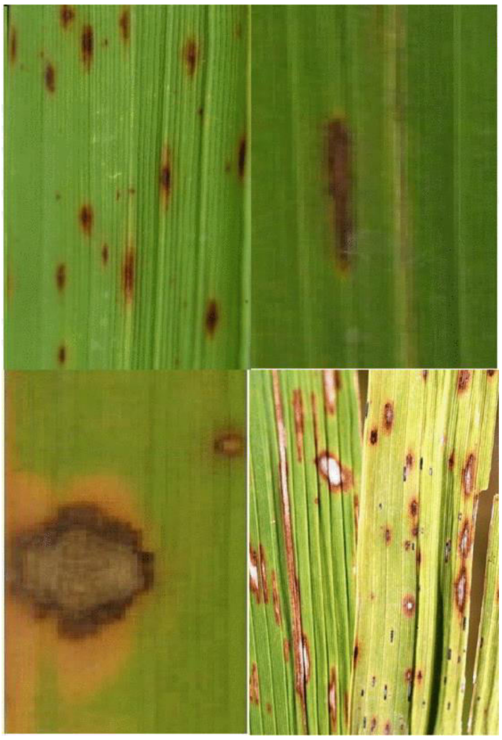

Fig. 7 Disease of the paddy leaves

To evaluate the capabilities of the proposed approach, the accurateness, sensitivity, and specificity of the proposed methodology were compared to other methods. Figure 8(a) shows that the proposed method achieved a extreme accuracy of 97.3%, that is 5.10% higher than the FA + FIS- leaf sorting, 6.60% higher than the algorithm based leaf disease sorting, and 7% higher than the FIS-based leaf disease sorting. This improvement is due to the fact that the entire FIS system was optimally selected using the variable step size firefly algorithm (VSSFA). The firefly algorithm (FA) is prone to getting stuck in resident optima, leading to poor accuracy. However, the proposed VSSFA method overcomes this limitation and produces high accuracy.

Likewise, in Figure 8(b), the method achieved the highest output sensitivity of 98.2%, compared to 95.36% for the FA + FIS-based method, 94.42% for the GA + FIS-based method, and 90.12% for the FIS-based method. Figure 8(c) shows the presentation in relationships of specificity. The proposed method achieved a maximum specificity of 100%, which is higher than the other methods. Overall, the results demonstrate that the proposed method outperforms the current methods in terms of accuracy, sensitivity, and specificity.

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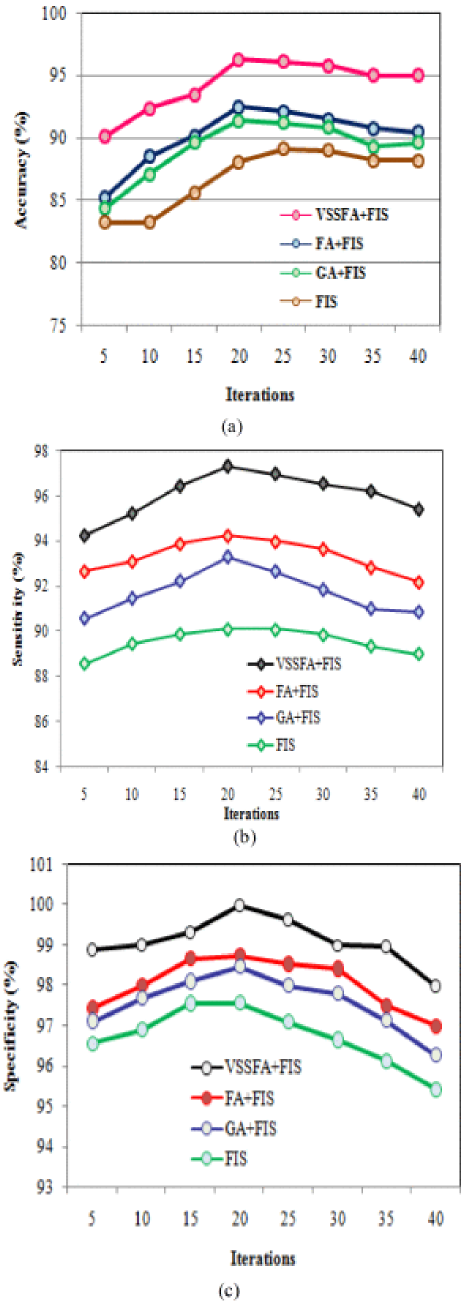

Fig. 8 result of the classification

CONCLUSION

In conclusion, this research presents an enhanced machine learning approach for identifying paddy crop blast disease management using fuzzy logic. The proposed approach utilizes a combination of feature extraction and classification techniques to accurately identify the presence of blast disease in paddy crops. The performance of the proposed approach was evaluated using a dataset of paddy images, and the results showed that it achieved high accuracy and sensitivity compared to other machine learning methods. The proposed approach has several advantages over traditional methods for paddy crop blast disease management. It is able to accurately identify the presence of blast disease at an early stage, which allows for timely intervention and management measures to be implemented. In

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addition, the use of fuzzy logic enables the system to handle uncertainty and imprecision in the data, which is often present in real-world situations.

Overall, the proposed enhanced machine learning approach has the potential to significantly improve paddy crop blast disease management, leading to increased crop productivity and profitability for farmers. Further research is needed to fully evaluate the effectiveness of the proposed approach in real-world scenarios and to explore its potential for use in other crop disease management applications.

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