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Paddy Crop Yield Prediction and Early Sheath Blight Disease Identification Using an Improved Grasshopper Optimization Algorithm-Based CNN (IGOA-CNN)

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Abstract

Therefore, in order to prevent or increase crop production, it is crucial to identify and successfully detect paddy crop illnesses at every step of a plant's life cycle. Initially, image preprocessing is done using bilateral filtering (BF) techniques. The semantic segmentation method is then used to segment the pre-processed images. The extracted segments are subjected to feature extraction. The feature data is extracted using the Scale-Invariant Feature Transform (SIFT) model. In this performance, an proposed Improved Grasshopper Optimization Algorithm-based Convolutional Neural Network (IGOA-CNN) with stochastic optimization method is described for both classifications and detection system of datasets gathered from the Kaggle Database at different stages of life, images that enable early detection of paddy crop yield infection even before the development of severe disease symptoms and healthy and Sheath Blight Disease. In order to reduce the use of chemicals and improve crop protection and productivity, an automatic pesticide spraying system is activated based on the detection results to only apply pesticides in affected areas. Paddy Crop Yield accuracy IGOA-CNN model: The proposed model was used to carry out the detection achieves 99.2% accuracy rate was attained.

Introduction

Paddy (Oryza sativa species) is still the primary source of energy and a vital component of proteins consumed by around three billion people at the beginning of the twenty-first century [1]. The 762 photos in the dataset were carefully prepared to prevent issues with an unbalanced dataset [2]. Support vector machine-recursive feature elimination (SV-RFE) and an adaptive rain optimization algorithm (ARO) are used to choose the features. The shared characteristics are then chosen [3]. Deep learning-based Convolutional Neural Network (CNN) method for the automated detection of rice leaf diseases [4]. The DST model under investigation attained 85% validation accuracy and 95% training accuracy. Multiple rice plant illnesses are detected by the researched model, which yields same results across multiple data sets [5].

Contribution of this Work

For more details, the following are the main steps of the suggested strategy:

- Preprocessing and Feature Extraction: Applied Bilateral Filtering (BF), semantic segmentation, and SIFT to enhance images and extract important

disease features from paddy crop images.
- Accurate Disease Detection: Developed an IGOA-CNN model to classify Healthy and Sheath Blight Disease crops, achieving 99.2% accuracy.
- Automatic Pesticide Spraying: Integrated a smart spraying system that targets only infected areas, reducing pesticide usage and improving crop yield.

The following describes the way the paper is established: Section 1 illustrates the introduction. The literature survey are described in Section 2. Section 3 explains the suggested techniques and Section 4 displays the findings of the experiment.

Literature Review

Mahadevan [6] et al. have proposed, in order to prevent financial and other resource waste, minimize yield loss, increase processing efficiency, and achieve healthy crop yields, the agricultural sector heavily relies on automatic rice disease detection and analysis. Subbarayudu [7] et al. have suggested, the hybrid Genghis Khan Shark Optimization (GKSO) with Simulated Annealing (SA) method is used to choose the essential features. The CatBoost is then used to classify diseases using the selected features. Zhang [8] et al. reported, the ReyTexFWave-based FFNN outperformed all single-feature extraction methods with an average accuracy of 94.84 ± 0.04%, 94.9% sensitivity, 88.7% precision, and 91.7% F-measure.

Proposed System

Figure 1 illustrates how the proposed method employs image processing and deep learning to detect rice crop diseases. To improve image quality and eliminate noise, the acquired crop image is first preprocessed using a bilateral filter. Important disease-related patterns are then extracted from the image using SIFT feature extraction. The IGOA-CNN algorithm then evaluates these characteristics to determine whether the crop is healthy or diseased such as sheath blight. For the purpose of making decisions, the affected areas are located and highlighted. An automatic pesticide spraying system is triggered based on the detection results to only apply pesticides in impacted areas, lowering the use of chemicals and enhancing crop protection and production.

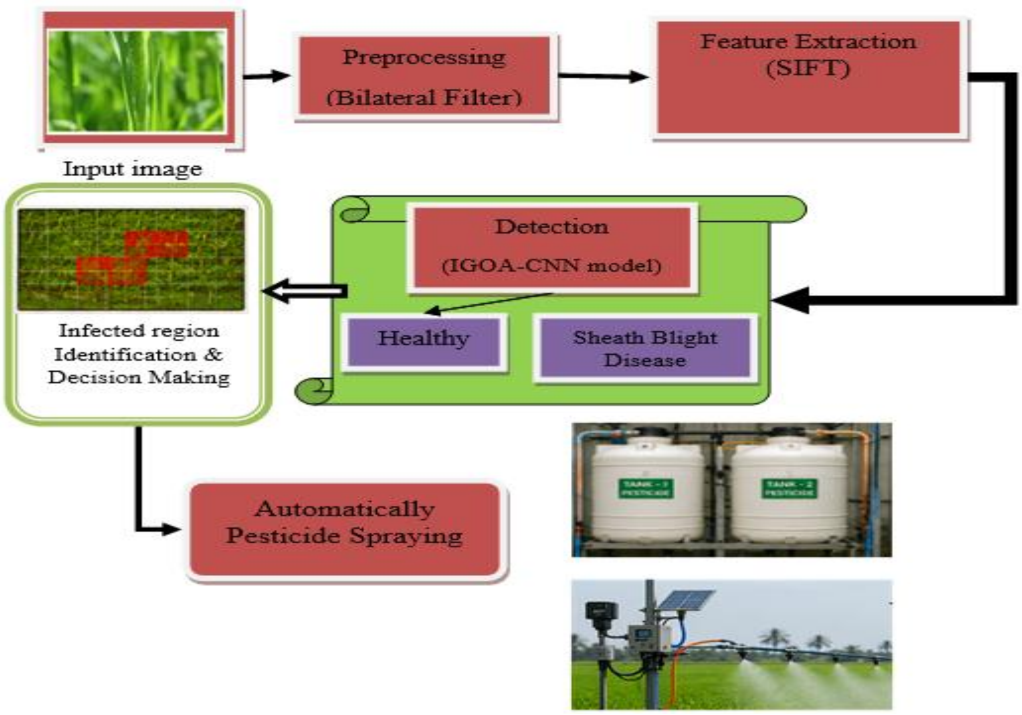

Figure 1. Proposed block diagram

1. Preprocessing using Bilateral filtering (BF)

The enhanced adaptive bilateral filter in our suggested method smoothes images while preserving edges by suggesting a nonlinear combination of close image values. Bilateral filtering is also non-iterative, "local," and straightforward despite being a nonlinear approach. It is possible to implement such a filter without solving a partial differential equation and in just one iteration. The spatial filter gs and the range filter gr, two Gaussian filters, could be combined to create the BF.

$$I_B = \frac{1}{W_n} \times \sum_{a_i \in \emptyset} \sum_{b_j \in \emptyset} I_{in}[(a - a_i), (b - b_i)] \times g_{\sigma_x}(a_i, b_j) \times g_{\sigma_y}[I_{in}(a_i), I_{in}(b_j)] \quad (1)$$

Where,

$$W_n = \sum_{a_i \in \emptyset} \sum_{b_j \in \emptyset} g_{\sigma_x}(a_i, b_j) \times g_{\sigma_y}[I_{in}(a_i), I_{in}(b_j)]-$$

represents the normalization factor.

2. Feature extraction using SIFT

To create a succinct depiction of an image, the SIFT examines the amplitude, alignment, and spatial closeness of visual fluctuations. It appears to be a predictor that is both rotationally and scaling inconsistent. When intriguing sites are found or identified, a potent description known as SIFT is produced. SIFT, on the other hand, can be used sparingly to generate a description across pre-selected intriguing areas. X^2 distance feature matching can be achieved using the following formula if 'a' and 'b' are the paddy crop leaf descriptors that:

$$X^2(a, b) = \sum w_j \frac{(a_{i,j} - b_{i,j})}{n + b_j} \quad (3)$$

3. Proposed IGOA based CNN Model for Detection

One of the most popular Meta heuristic techniques is the CNN model based on IGOA. This program was modeled after the swarm behavior of grasshoppers in their quest for food. Grasshoppers go through two stages: nymphs and adults. The way grasshoppers search for food served as inspiration for achieving the goal. The mathematical representation of IGOA is shown in the following equation:

$$X_i' = S_i' + G_i' + A_i' \quad (4)$$

The spot in which the i^{th} devised grasshopper is denoted by X_i'. S_i' is the sum of the social interaction, G_i' denotes gravity force and A_i'. The random behavior of this algorithm is achieved by adding random variables r_a, r_b, r_c in the range [0,1].

The modified version of the above equation is given as:

$$P_i^d = C\left(\sum_{\substack{j=1 \\ j\neq 1}}^{N} C\frac{ub_d - Ib_d}{2} S'\left(P_j^d - P_i^d\right)\frac{P_j' - P_i'}{d_{i,j}}\right) + \widehat{T_d} \quad (5)$$

Where, ub_d and Ib_d denotes the upper as well as lowest limits of the d^{th} dimension correspondingly. $\widehat{T_d}$ Represents the highest result in the d^{th} dimension space thus far. The flowchart for the CNN detection algorithm based on IGOA is displayed in Figure 2.

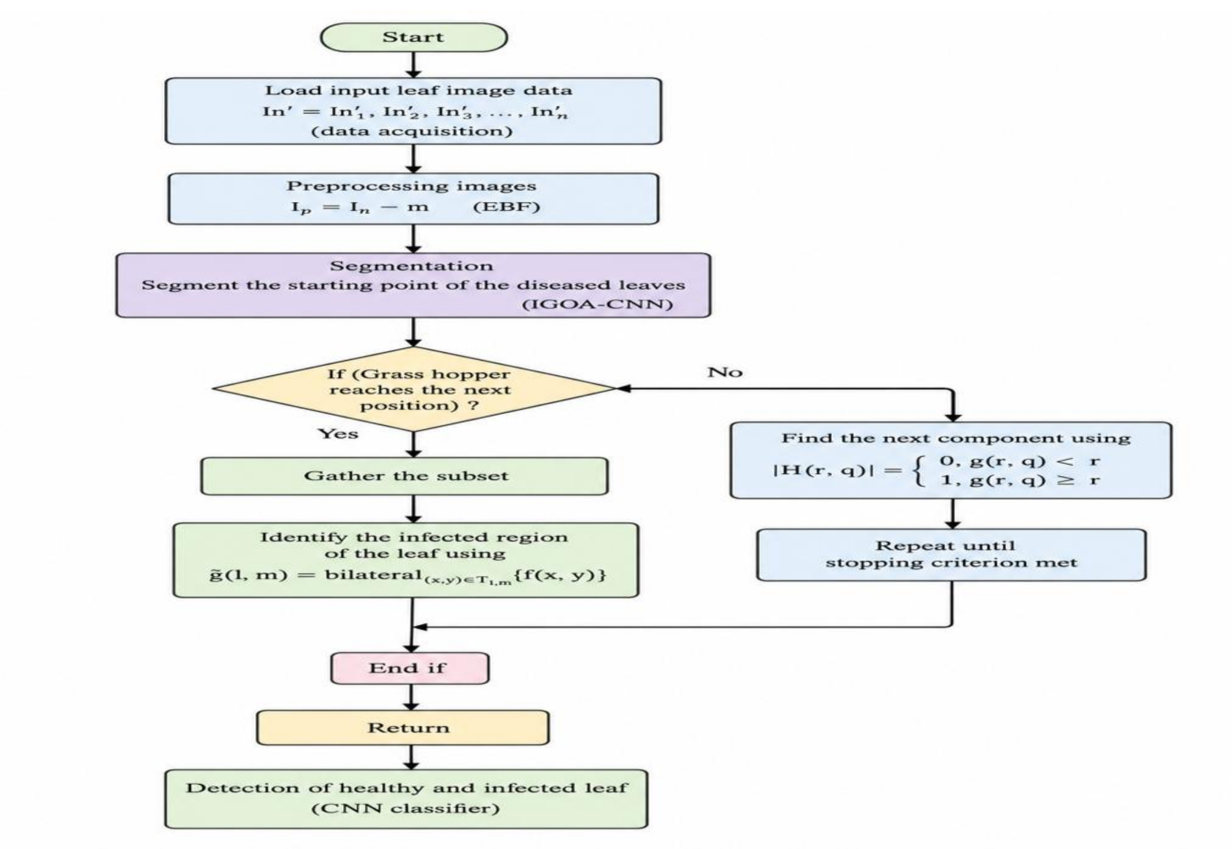

Figure 2. Flowchart for IGOA based CNN model for detection

Results and Discussions

Images of rice leaves from farms in various parts of India were gathered into a Kaggle dataset. Images of both healthy leaves and leaves with two different diseases sheath blight and healthy leaves are included in the dataset. To ensure variation, the photos were taken from different viewpoints and in different lighting. 70% of the images were used for training and 30% for testing when the dataset was divided into training, validation, and test sets. The paddy leaf diseases of a) healthy leaves and b) sheath blight disease are depicted in Figure 3.

Figure 3. Paddy Leaf Disease of a) Healthy leaf b) Sheath Blight Disease

Figure 4 display the an overall accuracy of 99.2%, the confusion matrix displays how well the disease classification model performs in differentiating between healthy and Sheath Blight Disease paddy leaves. Just 8 of the healthy samples were mistakenly labeled as Sheath Blight, compared to 992 that were correctly classified as Healthy. In a similar vein, only one sample was incorrectly labeled as healthy out of the 991 diseased samples that were correctly recognized as Sheath Blight Disease. Table 1 displays the comparison in proposed and existing methodology.

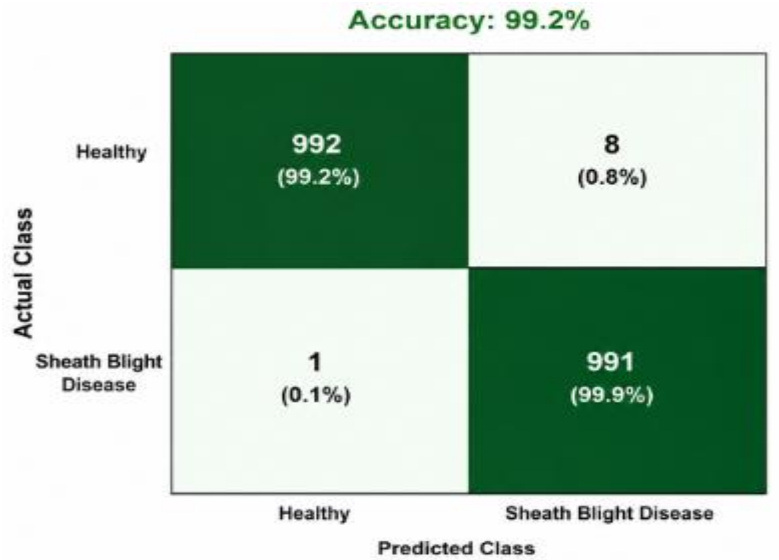

Figure 4. Confusion matrix for Paddy crop diseases detection

Table 1. Comparison of the effectiveness for multiple detection techniques

S.No	Method Used	Disease Type	Accuracy (%)
1.	EfficientNet-B0 [9]	Brown Spot, Blast	97.85
2.	MobileNetV2 [10]	Leaf Blast, Sheath Blight	98.10
3.	Proposed (IGOA based CNN model)	Healthy, Sheath Blight	99.2

Conclusion

For precise illness diagnosis, the suggested paddy disease detection system successfully integrates the IGOA-CNN model with SIFT feature extraction and bilateral filtering. With a 99.2% accuracy rate, the model was able to distinguish between photos of healthy and sick blight. Targeted treatment of affected regions is made possible by the incorporation of an automatic pesticide spraying system. Paddy output is increased, crop protection is improved, and pesticide waste is decreased. All things considered, the technology offers a clever and effective answer for precision farming. The method can be expanded in the future to identify several crop illnesses in real-world settings. For real-time monitoring, the framework can be coupled with IoT sensors and UAVs.

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