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A Machine Intelligent Framework for Detection of Rice Leaf Diseases in Field Using IoT Based Unmanned Aerial Vehicle System

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Abstract

Rice is an important food in our day-to-day life. It has rich sources of carbohydrates that are highly essential for body growth and development. Rice is an important crop in agriculture, where it enhances a country's economy. However, if rice plants are diseased and not monitored regularly then the crop in the field is wasted and it reduces the proper production rate. Therefore, there should be a mechanism which regularly monitors the crop in a field to detect any disease to rice plant. In this paper, a framework is proposed for identification of rice leaf disease using IoT based Unmanned Aerial Vehicle (UAV) system. Here, the UAV monitors an entire field, capture the images and sends the images to the machine intelligent cloud for detection of rice leaf diseases. The cloud is installed with a proposed stacking classifier that classify the diseased rice plant images received from UAV into different categories. The dataset of these rice leaf diseases is collected from Kaggle source. The performance of the stacking classifier installed at the cloud is evaluated using Python based Orange 3.26 tool. It is observed form the results that stacking classifier outperforms the conventional machine learning models in detecting the actual disease with a classification accuracy (CA) of 86.7%.

Keywords: Rice, Disease Detection, IoT, UAV, Machine Learning, Stacking Classifier.

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1. Introduction

Rice is a food that is very much essential for human life. It has rich sources of carbohydrates that is very much essential to human body development. Rice crop is also important to country's economy development where the farmers in all the countries are mainly dependent on this crop [1,2]. However, due to climatic conditions and many environmental factors the rice plant is affected with many diseases [3]. So, there should be design or framework where the rice plant field is monitored periodically to check the happening of these diseases at any time duration in the life cycle of the rice plant.

UAV [4,5] is an application of drone technology where the UAVs are now mainly used for many purposes such as surveillance, loading and unloading, agriculture for sprinkling insecticide and pesticide, disaster management, etc. As the main purpose is surveillance, it motivated us to choose UAV in the framework, where the UAV in the field can capture the images, and using Internet of Things (IoT) it sends the image data to the cloud for storage and detection. Here, IoT [6-8] plays are important role as it is now the most demanding technology for users to use this sensor-based technology. IoT is connected with different sensors for measuring the physical environment and uses Internet capability to send these data to another node or network. Therefore, in this framework we have choses IoT as an important component for better data communication process.

Nowadays cloud computing [9,10] plays important role in providing many services to the users like platform computing, platform, infrastructure, software, etc. So, in this model as UAVs have limited power supply, storage and computational capability, the image data is forwarded to cloud for processing and storage. Therefore, cloud computing is an important component in this framework and design. Cloud is now becoming more intelligent to process the complex tasks using artificial technology (AI) technology. The AI technology has many algorithms for solving the classification, regression, and clustering problems. The algorithms mostly used in machine learning (ML) [11-27] are supervised, unsupervised, and hybrid. So, ML is also an important component of the proposed design where the classifier installed in the cloud will detect the actual disease.

The contributions to this paper are shown below:

1. A framework is proposed for identification of rice leaf disease using IoT based UAV system. Here, the UAV monitors an entire field, capture the images and sends the images to the machine intelligent cloud for detection of rice leaf diseases.
2. The cloud is installed with a proposed stacking classifier that classify the diseased rice plant images received from UAV into different categories. The dataset of these diseases is collected from Kaggle source [3].
3. The performance of the stacking classifier installed at the cloud is evaluated using Python based Orange 3.26 tool. It is observed from the results that proposed stacking classifier outperforms the conventional ML models in detecting the actual disease with a CA of 86.7%.

The remaining portions of the work are presented as follows. The next followings sections Section 2 to Section 5 discusses about related work, methodology, simulation and conclusion respectively.

2. Related Work

The related research to this work is discussed as follows. Ahmed et al. [28] studied the performance of ML techniques on detection of rice leaf disease. Ouhami et al. [29] studied the application of IoT, data fusion, and computer vision for rice disease detection. Kitpo et al. [30] et al. used drone and IoT for rice disease detection and mapping the position. Li et al. [31] recognized the rice images of UAV in capsule network. Rathore et al. [32] used convolution neural network for automatically recognizing and detecting the rice plant disease detection. Cai et al. [33] spotted the brown leaf sot severity in rice images collected from UAV. Crimaldi et al. [34] used UAVs to detect the plant diseases through neural network algorithm.

From the above study, it is found that very less work has been done in the area of machine intelligent cloud framework, where the cloud is installed with a best ML model for classification of leaf diseases. The computational capability of IoT and UAV is less therefore the computations in our model is processed in cloud.

3. Methodology

The system framework as shown in Fig. 1 mainly consists of the two layers such as device and cloud. In the device layer the main component is UAV that is controlled by a user or farmer over the rice field. The UAV has camera sensor which captures the rice plant images and by using IoT the images are sent to the cloud through base station (BS). The BS can send and receive the data wirelessly. The UAV uses the IoT for Internet capability to connect with the cloud. The UAV has limited computational and storage capability. The cloud node in the cloud layer is responsible for storage of rice plant images of a field and processing of these images for detection of rice plant diseases using stacking classifier. The cloud has high computational and storage capability. The cloud node and IoT based UAV use wireless communications for data communication.

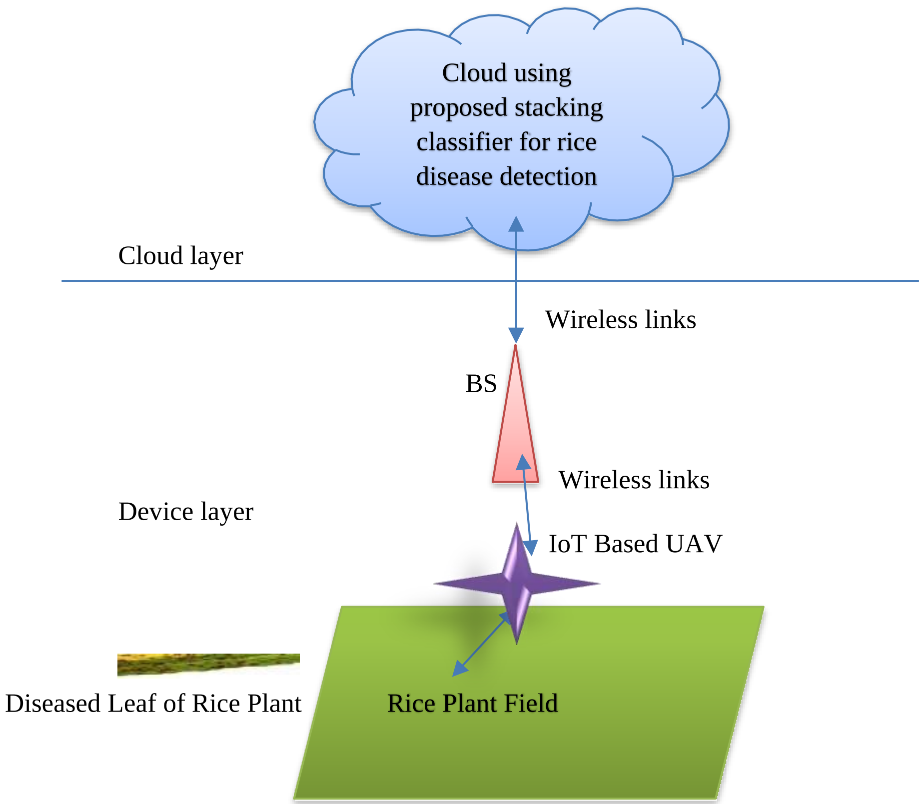

Fig. 1: System architecture framework

The step-by-step process for rice plant disease detection is stated below and shown in Fig. 2:

Step 1: The user starts the UAV for capturing the rice plant field images.
Step 2: The images are continuously sent to nearest BS using Internet.
Step 3: BS sent the images to the cloud for detection of rice plant disease.
Step 4: The cloud receives the images and store it in the local storage.
Step 5: Images are taken into the stacking classifier that is installed in the cloud node for detection or classification of images. The stacking classifier model is clearly discussed below with representation in Fig. 3.
Step 6: The classifier label is: particular leaf disease
Step 7: The information is updated to the user through a warning message if these types of diseases are detected at cloud.

Step 8: The message is forwarded to the IoT based UAV through nearest BS for taking action in emergency.

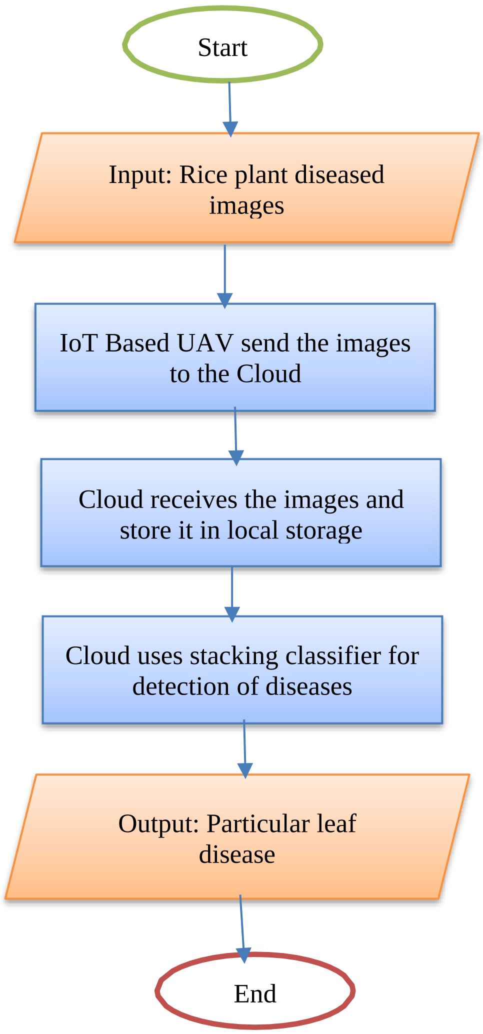

Fig. 2: Flowchart of complete proposed work

The stacking classifier is built by considering some existing ML models as shown in Fig. 3. The Logistic Regression here acts as the aggregator of all models and all other models are the data learners. The selection of these algorithms is based on the CA of these models which are quite high after testing these models through a standard dataset [3]. This hybridization helps to detect the diseases at more accuracy.

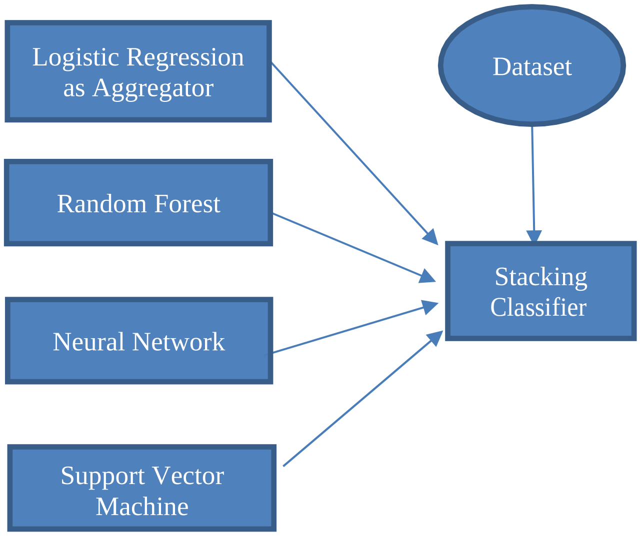

Fig. 3: Design of stacking classifier for installation at cloud

4. Simulation Results

The performance of the stacking classifier used in this framework is assessed using Python based Orange 3.26 tool [35]. The machine in which this performance is assessed has 8 GB RAM and 2.4 GHz processor speed with 64-bit Win-OS.

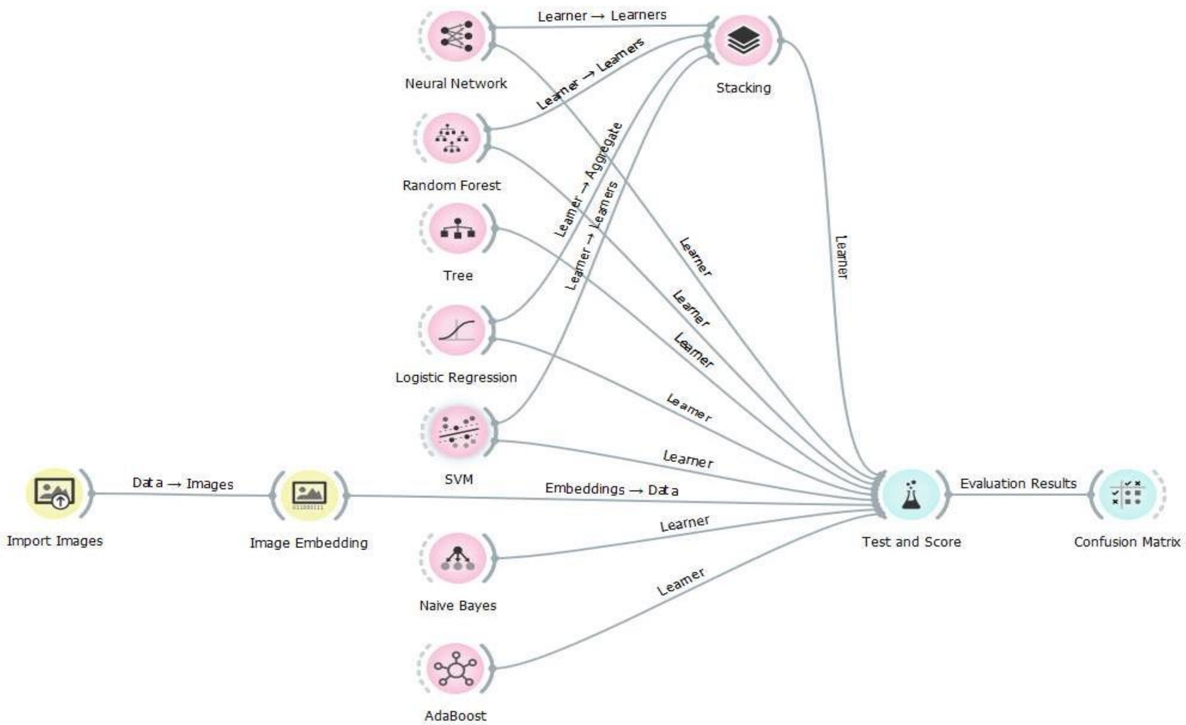

Fig. 4: Orange workflow setup diagram

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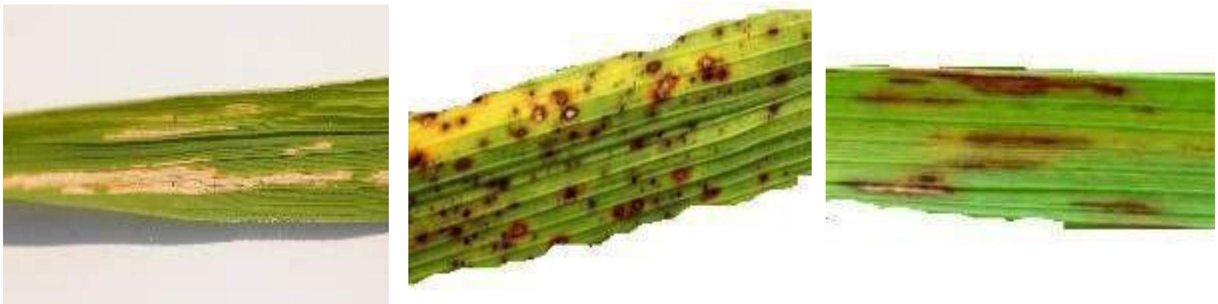
The workflow of the orange tool is designed in Fig. 4. The default supervised machine learning models in the Orange tool are selected for this simulation. The stacking classifier is also built using the tool as shown in Fig. 4. The performance metric taken is CA = Number of Actuals Predicted Correctly / Total Number of Actuals. The training and testing size is kept to 80:20 with random sampling technique is used.

The dataset is collected from Kaggle source [3]. There are total 120 images in the dataset of which bacterial leaf blight (BLB), brown spot (BS), and leaf smut (LS) category of rice plant diseases have 40 images each. The images are trained and tested as per the default settings of each model in Orange tool [35]. In Fig. 5 the image category taken are shown. We assume that these images are taken from UAV as per our system architecture framework.



(a) BLB (b) BS (c) LS

Fig. 5: Sample images of different rice leaf plant disease [3]

Table 1 shows the CA comparison of ML models taken. It is observed from the results that proposed stacking classifier and other models shown in Table 1 serially show the CA of 0.713, 0.825, 0.796, 0.858, 0.742, 0.850, 0.729, and 0.867 respectively. So, from the CA values it is seen that proposed stacking classifier show better detection accuracy of 86.70% then other ML approaches. The comparison of CA of all models are clearly represented in Fig. 6. The confusion matrix (CM) of all the models for visualization of actuals and predicted are shown in Figures 7-14.

Table 1: Comparison of CA of different ML models

Sl. No.	Method	CA
1	Tree	0.713
2	Support Vector Machine	0.825
3	Random Forest	0.796
4	Neural Network	0.858
5	Naïve Bayes	0.742
6	Logistic Regression	0.850
7	AdaBoost	0.729
8	Proposed stacking classifier	0.867

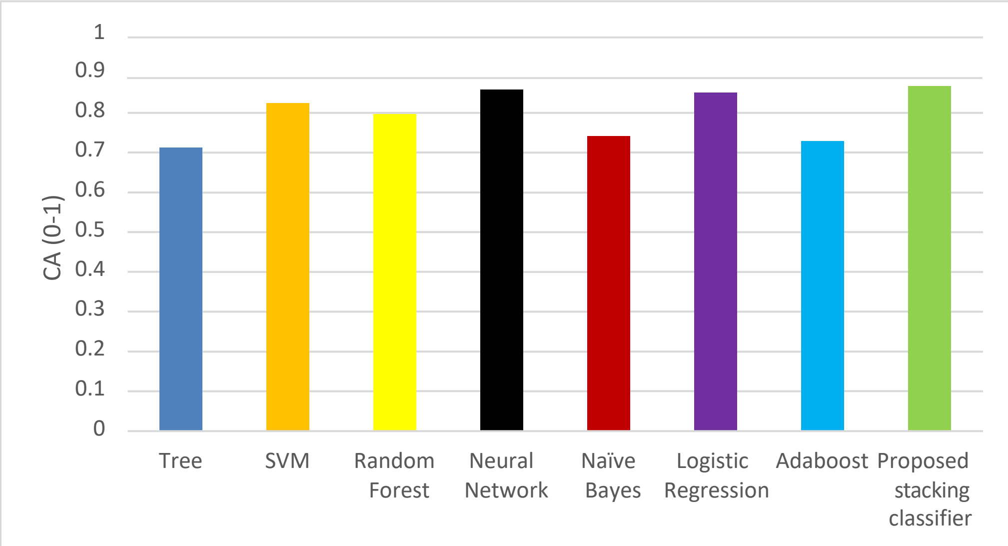


Fig. 6: Comparison of CA of all models

Actual \ Predicted	Bacterial leaf blight	Brown spot	Leaf smut	Σ
Bacterial leaf blight	59	7	14	**80**
Brown spot	17	55	8	**80**
Leaf smut	9	14	57	**80**
Σ	**85**	**76**	**79**	**240**

Fig. 7: CM for decision tree

Actual \ Predicted	Bacterial leaf blight	Brown spot	Leaf smut	Σ
Bacterial leaf blight	71	5	4	**80**
Brown spot	11	60	9	**80**
Leaf smut	7	13	60	**80**
Σ	**89**	**78**	**73**	**240**

Fig. 8: CM for random forest

Predicted

Actual	Bacterial leaf blight	Brown spot	Leaf smut	∑
Bacterial leaf blight	76	2	2	**80**
Brown spot	11	65	4	**80**
Leaf smut	9	14	57	**80**
∑	**96**	**81**	**63**	**240**

Fig. 9: CM for support vector machine

Predicted

Actual	Bacterial leaf blight	Brown spot	Leaf smut	∑
Bacterial leaf blight	73	4	3	**80**
Brown spot	8	65	7	**80**
Leaf smut	6	8	66	**80**
∑	**87**	**77**	**76**	**240**

Fig. 10: CM for logistic regression

Predicted

Actual	Bacterial leaf blight	Brown spot	Leaf smut	∑
Bacterial leaf blight	72	6	2	**80**
Brown spot	19	57	4	**80**
Leaf smut	11	20	49	**80**
∑	**102**	**83**	**55**	**240**

Fig. 11: CM for Naïve Bayes

Predicted

Actual	Bacterial leaf blight	Brown spot	Leaf smut	∑
Bacterial leaf blight	60	12	8	**80**
Brown spot	12	58	10	**80**
Leaf smut	10	13	57	**80**
∑	**82**	**83**	**75**	**240**

Fig. 12: CM for AdaBoost

Actual \ Predicted	Bacterial leaf blight	Brown spot	Leaf smut	Σ
Bacterial leaf blight	74	3	3	**80**
Brown spot	4	70	6	**80**
Leaf smut	6	12	62	**80**
Σ	**84**	**85**	**71**	**240**

Fig. 13: CM for neural network

Actual \ Predicted	Bacterial leaf blight	Brown spot	Leaf smut	Σ
Bacterial leaf blight	73	4	3	**80**
Brown spot	4	71	5	**80**
Leaf smut	6	10	64	**80**
Σ	**83**	**85**	**72**	**240**

Fig. 14: CM for proposed stacking classifier

5. Conclusion

A framework is proposed to identify rice plant disease using IoT based UAV system. Here, the UAV monitors the entire field, capture the images and sends the images to the machine intelligent cloud for detection of rice leaf diseases. The cloud is installed with a proposed stacking classifier that classify the diseased rice plant images received from UAV into different categories. The performance of the stacking classifier installed at the cloud is assessed using Python based Orange tool. It is observed from results that stacking classifier outperforms the conventional machine learning models in detecting the actual disease with a CA of 86.7%. In future, we will work in improving CA, proposing new hybrid models, and taking new large datasets for analysis.

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