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Classification of Rice Pest Data Using Decision Tree Algorithm

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Abstract: Data mining can be defined as the process of selecting, exploring and modeling large amounts of data to uncover previously unknown patterns. Data Mining is an emerging research field in the analysis of agricultural data. Classifications of data have been successfully applied in various applications. Classification of large volume of data especially in agriculture is a challenging task. One of the major challenges in agriculture data analysis is the prediction of prognosis, especially in pest data to determine the control measures. Decision tree method is generally used for the classification, because it is the simple hierarchical structure for the user understanding and decision making. In the present study, the various classification techniques have been applied with *Leaf Folder* pest data set of rice crop, for classifying them into four categories based on pest intensity range during the entire cropping season, using R statistical language.

In this paper the decision tree classification techniques as well as main issues in classifying and predicting methods for agriculture data have been reviewed. In addition to the above the performances of the various classification techniques have also been presented.

Keywords - C4.5 Classification, Data mining, Decision Tree Classification, Rice Pest data.

1. INTRODUCTION

Data Mining is the process of discovering the interesting patterns or information from the data in large databases. The data sources can include databases, data warehouses, the Web, other information repositories, or data that are streamed into the system dynamically. Han and Kamber (2005) had defined the data mining as knowledge discovery in databases, knowledge extraction, pattern analysis, data archeology, business intelligence as shown in figure 1.

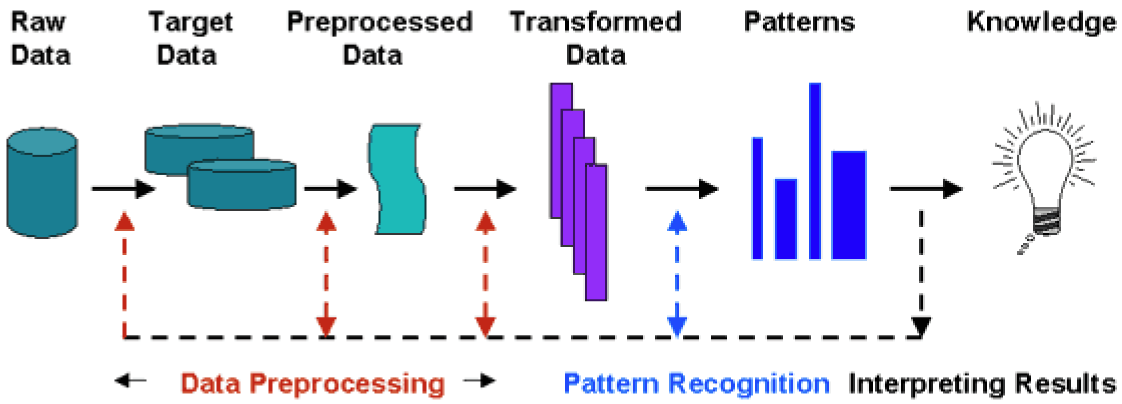


Figure 1: The Process of Knowledge Discovery in Database

Alagukumar and Lawrance (2015a & b), stated that data mining techniques have become a popular tool for analyzing large amount of data. Srinivasan and Aggarwal (2003) had discussed that, data mining techniques have become a popular research tool for agriculture data to identify and exploit patterns and relationships among large number of variables, and to predict the outcome of a pest using the historical datasets.

Priyam *et al.*, (2013) applied ID3, C4.5, and CART algorithms on the educational data for predicting the student's performance in examination. The algorithms are applied on student's internal assessment data to predict their performance in the final exam. They mentioned that C4.5 is the best algorithm for small datasets because it provides better accuracy and efficiency than other algorithms.

Hssina *et al.*, (2014) have focused on the key elements of their construction from a set of data and then they presented the algorithm ID3 and C4.5 that respond to classification. Finally they compared ID3 and C4.5, which confirmed that the most powerful and preferred method in machine learning is certainly C4.5.

One of the major challenges in agriculture data analysis is the prediction prognosis especially in pest data to determine the control measures. In the current study the *Leaf Folder* pest data set of rice crop collected throughout Maharashtra state under Crop Pest Surveillance and Advisory Project (CROPSAP) during

2009-2013 was used and various classifying techniques / algorithms were tested to find out the suitable and effective technique for classifying the pest data based on pest intensity range during the entire cropping season in to four categories.

2.MATERIALS AND METHODS

Classification technique plays a vital role in agricultural data experiments, for purposes of classifying pest samples and prediction using agricultural pest data. The Classification System of decision tree (C4.5) on agriculture data is shown in figure 2.

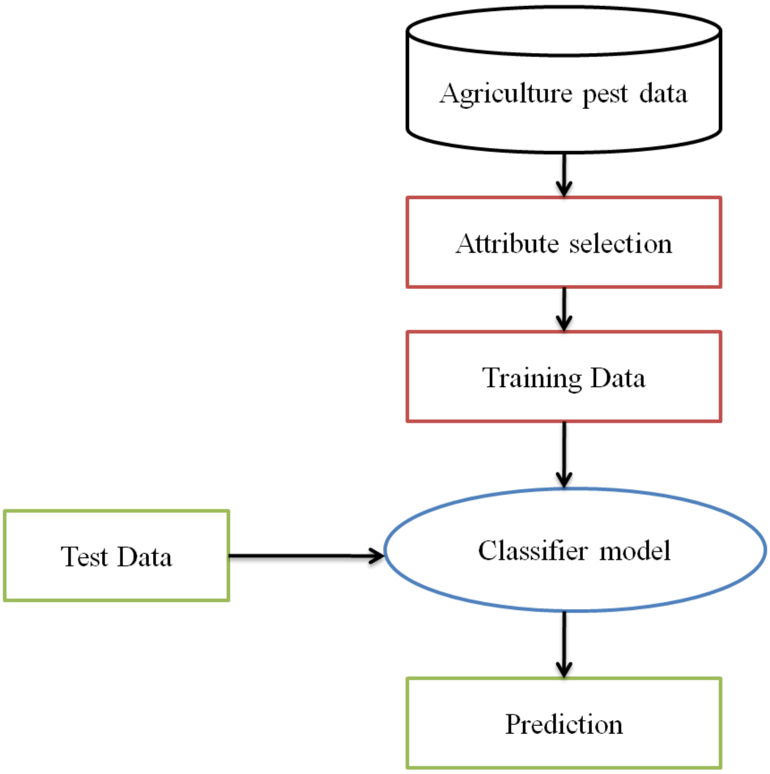


Figure 2: The Classification Approach

A. *Data formats*

In the present study the *Leaf Folder* pest data set of rice crop recorded at farmers' fields from various villages of Maharashtra under Crop Pest Surveillance and Advisory Project (CROPSAP) has been used. The dataset can be in the form of a M x N matrix D, where the row X={ x1,x2,x3… xm} represents the fields / villages and column P={p1,p2,p3…, pn} represents pests as shown in Table 1.

Table 1: Agriculture pest Data

Samples	Attributes				Category by pest intensity
	P_1	P_2	…	P_n	
x1	p(1,1)	p(1,2)	…	p(1,n)	White
x2	p(2,1)	p(2,2)	…	p(2,n)	Green
x3	p(3,1)	p(3,2)	…	p(3,n)	Yellow
…	…	…	…	…	Red
…	…	…	…	…	Green
xm	p(m,1)	p(m,2)	…	p(m,n)	Yellow

Category column represents the actual class of the pest sample based on pest intensity. For the current study *Leaf Folder* pest data set of rice crop of Vidarba district of the State of Maharashtra is used, where they are classified based on pest intensity expressed as number of folded leaves per hill. Based on pest intensity, data is classified as white (pest intensity < 25%), green (pest intensity between 25% and 50%), yellow (pest intensity between 50% and 75%) and red (pest intensity >= 75%).

B. *Classification Techniques*

Classification is a task performed to generalize known structure in data mining to apply to new data. It is also the categorization of data for its most effective and efficient use. There are numerous data mining classification algorithms being studied and implemented in different domains.

Han and Kamber (2005) discussed that classification is a data mining technique which assigns an object to one of several predefined categories based on the attributes of the object. The input dataset termed as the training data set, which contains the number of predefined labels each having a number of attributes. The attributes are either continuous or categorical. The main aim is to use the training data set to build a model, which can be used to classify unknown label data set.

C. Decision Tree

Han and Kamber (2005) have also stated that Decision Tree is a supervised classification, which predicts both the classifier and regression models. Classification trees are mainly used to classify an object to a predetermined class based on the attributes. Safavian and Landgrebe (1991), surveyed classification techniques and explained the classification trees. A Tree is a set of nodes, a node with no incoming edge and zero or more outgoing edge is called as Root, a node with exactly one incoming edge and one or more outgoing edge is called as Internal node and all other nodes are known as Leaf node which has exactly one incoming edge and no outgoing edge. Using the Training set the classifier model has been developed; testing set was applied on the classification model to predict the previously unknown class.

Raorane, A, A. et. al. (2012) has discussed that Decision tree is one of the classification algorithms which can be used in Data mining. Learning decision tree is paradigm of inductive learning. A model is built from data or observations according to some criteria. The model aims to learn a general rule from the observed instances. Decision trees can therefore accomplish two different tasks depending on whether the target attribute is discrete or continuous.

C4.5 is one of the Decision tree Classification Algorithms developed by Quinlan(1996 & 2014). It uses Gain ratio as a Splitting Criteria by calculating entropy and splitting information of an attribute. It can handle numeric attributes and missing values. The C4.5 decision tree classification is faster than ID3 algorithm and also ID3 cannot deal with missing values. Decision tree is constructed by examining a set of training samples whose class labels are known. These features of known samples are applied in order to determine the properties of unknown samples. The C4.5 Classification Algorithm provides accurate result, takes less memory space for large data set, less time to build a model and has short searching time.

D. Algorithm : Decision Tree Classification

Let the class label be represented as $\{C_1, C_2, \ldots, C_k\}$. There are number of possibilities for the content of the set of training samples T in the given node of decision tree. If S is any set of samples, let $f(C_i, S)$ stand for the number of samples in S that belong to class C_i(out of k possible classes), and $|S|$ denotes the number of samples in the set S. Then the entropy of the set S:

$$Info(s) = -\sum_{i=1}^{k}\left(\left(\frac{f(C_i, S)}{|S|}\right) * \log_2\left(\frac{f(C_i, S)}{|S|}\right)\right)$$

After set T has been partitioned in accordance with n outcomes of one attribute test X:

$$Info_x(T) = \sum_{i=1}^{n}\left(\left(\frac{|T_i|}{|T|}\right) * info(T_i)\right)$$

Criterion: then select an attribute with the highest gain value

$$Gain(X) = Info(T) - info_x(T)$$

Input:

D, Training dataset with class labels

Output:

Generates Decision tree Classification model for predicting results.

Classification Model Construction Procedure:

Begin

Step1. Read the training dataset from agricultural pest data
Step2. Compute entropy value for all attributes
Step3. Select best attribute having highest gain ratio according to the entropy value
Step4. Create a decision node based on the best attribute in step 3
Step5. Split the dataset based on newly created decision node in step 4
Step6. For all sub-dataset in step 5, call the algorithm recursively to get a sub-tree
Step7. Attach the tree obtained in step 6 to the decision node in step 4
Step8. Return tree
Step9. Decision tree Classification model for predicting result is the output

End

3. RESULTS & DISCUSSION

In this study the above discussed method has been implemented with the *Leaf Folder* pest data set of rice crop collected from the district Vidarba under CROPSAP Project of the State of Maharashtra. The experimental research was implemented using R statistical language. The R software can be downloaded from the link https://cran.r-project.org/. The experimental dataset has huge volume of data regarding the pests and other relevant information. The research implements the decision tree classifications and other traditional classification algorithms for the rice pest dataset. Table 2 shows the sample data and figure 3 shows the working of the decision tree.

Table 2: Sample Data

Taluka	Leaf Folder Pest count	Range
T1	0.2811	Yellow
T2	0.2656	Green
T3	0.0240	White
T4	0.2000	Green
T5	0.5515	Red
T6	0.2516	Green
T7	0.3008	Yellow
…	…	…

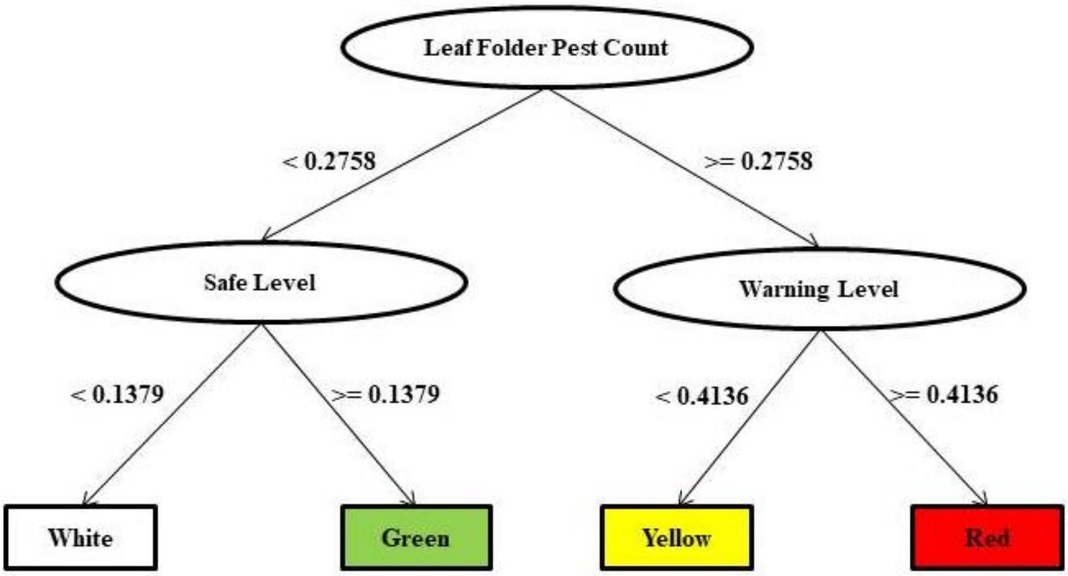


Figure 3: Working of Decision Tree

Confusion matrix is a visualization tool which is commonly used to present the accuracy of the prediction. The confusion matrix is represented in table 3.

Table 3: Confusion Matrix

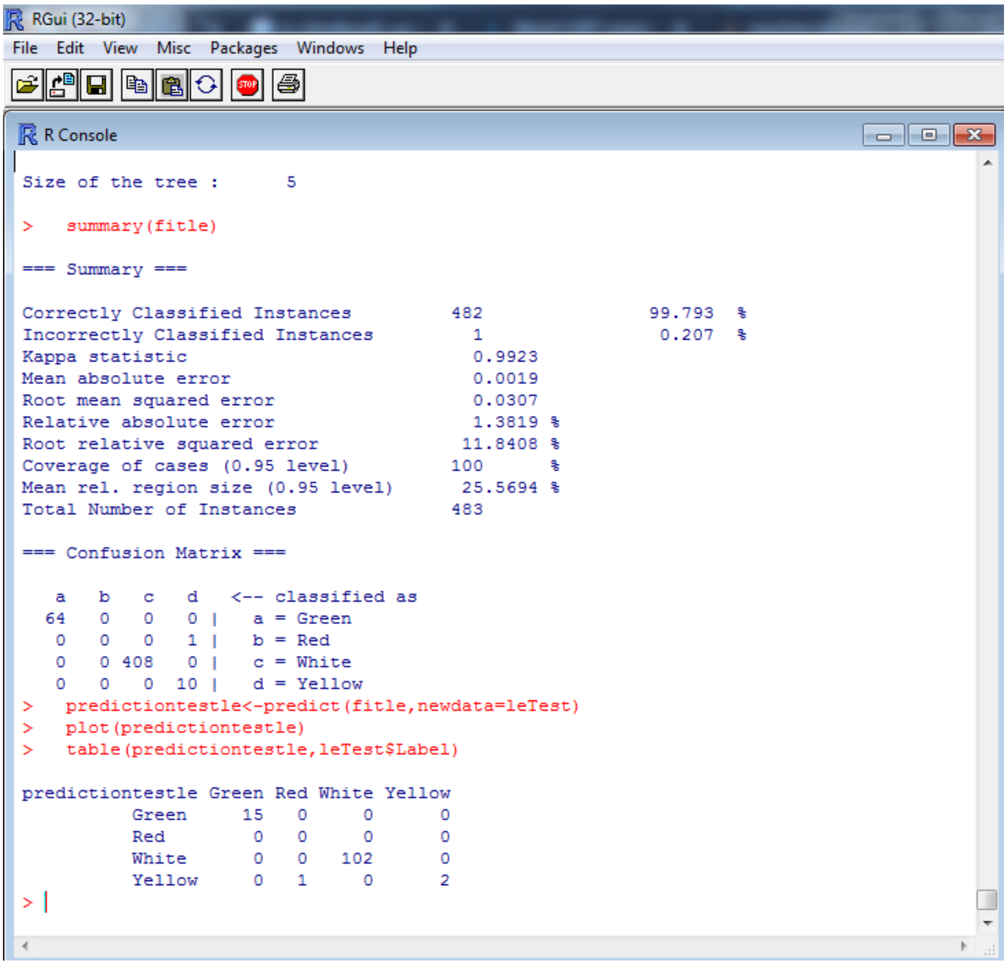
	Predicted Class	
Actual Class	TP	FN
	FP	TN

The confusion matrix is used to show the relationship between outcomes and predicted classes. The effective classification model is calculated with number of correct and incorrect classifications for each possible value of the variable being classified in the confusion matrix. The accuracy of a classifier for a given test set is the percentage of test set tuples that are correctly classified by the classifier.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$ErrorRate = \frac{Number\ of\ wrong\ predictions}{Total\ number\ of\ predictions} = \frac{FP + FN}{TP + TN + FP + FN}$$

In this study the various classification techniques have been applied and experimented with the *Leaf Folder* pest data set of rice crop. The Classification System of decision tree (C4.5) on agriculture data is shown in figure 2. Normally the classification techniques are divided into two parts such as training phase and test phase. This represents the classification and prediction step of the present system. Initially the agriculture pest data has been passed as training data set. The best attributes have been selected using entropy value and selected attributes have been used to generate the tree and form the classification model. Finally the test data have been passed into the classification model and predict the pest level for agricultural rice data set using R language as shown in the figure 4.



```
RGui (32-bit)
File  Edit  View  Misc  Packages  Windows  Help
R Console

Size of the tree :      5

>   summary(fitle)

=== Summary ===

Correctly Classified Instances         482               99.793  %
Incorrectly Classified Instances         1                0.207  %
Kappa statistic                          0.9923
Mean absolute error                      0.0019
Root mean squared error                  0.0307
Relative absolute error                  1.3819 %
Root relative squared error             11.8408 %
Coverage of cases (0.95 level)         100      %
Mean rel. region size (0.95 level)      25.5694 %
Total Number of Instances              483

=== Confusion Matrix ===

   a   b   c   d   <-- classified as
  64   0   0   0 |   a = Green
   0   0   0   1 |   b = Red
   0   0 408   0 |   c = White
   0   0   0  10 |   d = Yellow
>   predictiontestle<-predict(fitle,newdata=leTest)
>   plot(predictiontestle)
>   table(predictiontestle,leTest$Label)

predictiontestle Green Red White Yellow
          Green     15   0     0      0
          Red        0   0     0      0
          White      0   0   102      0
          Yellow     0   1     0      2
> |
```

Figure 4: Prediction of the Pest Intensity

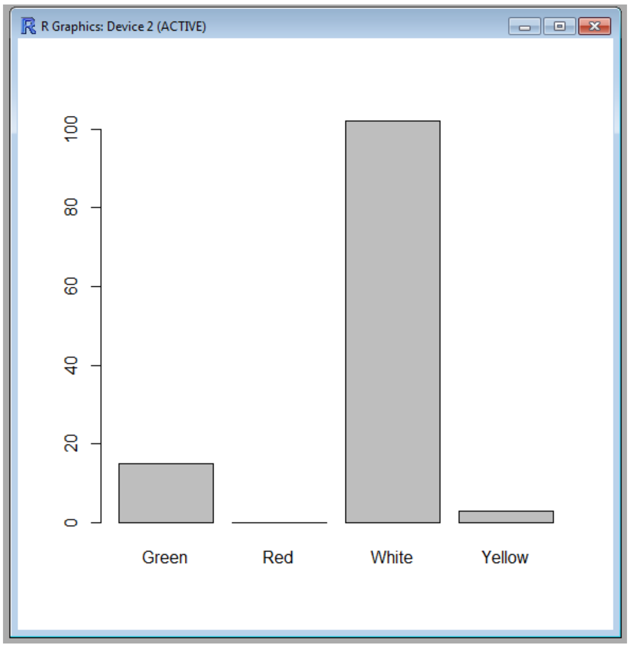


Figure 5: Graphical presentation of the Prediction

The figure 5 represents the visualization of the classification based on pest intensity. Here the *Leaf Folder* pest data set of rice crop is classified, such as white, green, yellow and red based on the pest intensity range values as explained in the previous section.

The accuracy of the different classifiers on the rice crop pest dataset is presented in table 4, Out of six classification methods tested, it was found that C4.5 (decision tree) was effective with accuracy of 78%

followed by Naïve Bayes and kNN algorithms both with 72 % accuracy.

Table 4: Comparative Analysis

Method	Accuracy on Agriculture data
C4.5 (Decision Tree)	78 %
RIPPER (Decision Tree)	60 %
Oblique (Decision Tree)	50 %
Naïve Bayes	72 %
kNN	72 %
LDA	46 %

The various classification algorithms are tested with Iris Flower bench mark dataset and tested how it was performing with Decision tree classification algorithms. Finally, the classification algorithms are tested with rice crop pest dataset and calculated classification performance using accuracy measures. The figure 6 represents the comparative analysis of the decision tree classification performance with traditional classification algorithm for *Leaf Folder* pest data set of rice crop in comparison with Iris Flower bench mark dataset.

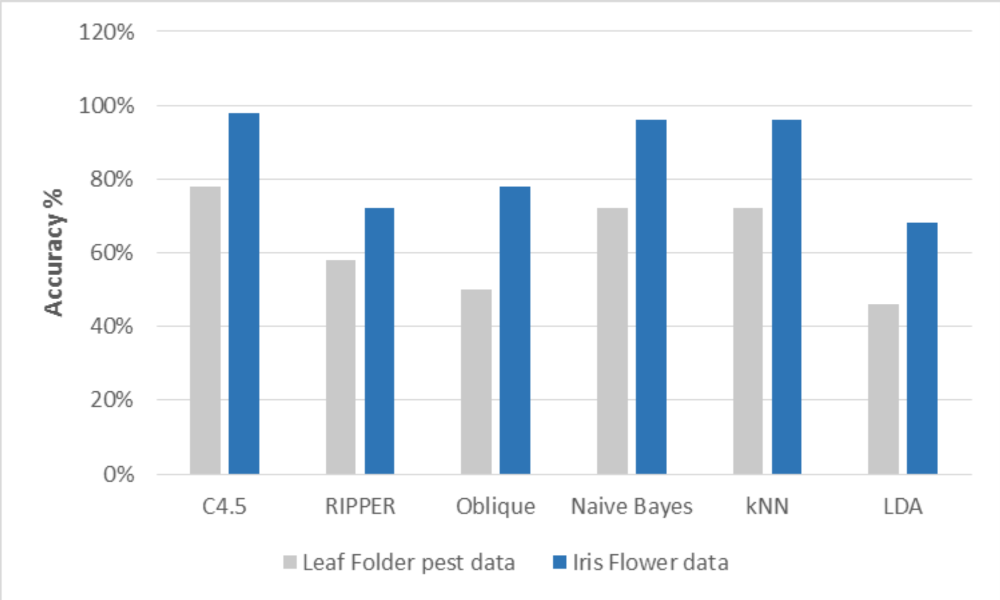


Figure 6: Comparative Analysis

Thus from the accuracy measures for the classification algorithms for the Iris Flower dataset and rice crop pest dataset, it can be observed that C4.5, Naïve Bayes and kNN classifiers are more accurate than the other classifiers. Priyam e*t al.* (2013) and Hssina *et al.* (2014) also confirmed the same. Also, the oblique decision tree classifier and LDA classifier is the least accurate for both the datasets. C4.5 is used in classification problems and it is the most used algorithm for building Decision tree. It is suitable for real world problems as it deals with numeric attributes and missing values. The algorithm can be used for building smaller or larger, more accurate decision trees and the algorithm is quite time efficient. Compared to ID3, C4.5 performs by default a tree pruning process, which leads to smaller trees, more simple rules and more intuitive interpretations. For the classification of agricultural pest data in to different classes C4.5 can be used, which gives more accurate classification system, thus enabling us to quickly classify the large volume of data into different classes assisting in quick pest management decision making.

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