A Classification Based Target Specific Expert System for Cotton Crop

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Abstract—Diseases detection at early stage helps the crops to overcome disease disorder and treat appropriately. Proposed work developed an expert system named Classification Based Target Specific Expert System (CTSES) used to identify the diseases at early stage. In this work CTSES finds the diseases in cotton crops. A rich knowledge base is developed. The knowledge base contains all the facts related to domain. Different rules are developed and used for inferencing. A fuzzy inferencing mechanism provides the reliability of occurrence of disease in cotton plant. The main feature of CTSES is a classification module which helps to determine the probability of occurrence of a disorder and the class to which the disorder belongs. The classification module serves at two level: (1) Classification and grouping of disorder, having same causing agents such as virus, bacteria, fungi etc., based on feature vector extraction technique. (2) Reclassification based on Support Vector Machines (SVM), as provided by the widely used 'libsvm' implementation. The classification module helps the system to find results faster from large database by reducing the number of searches and decreasing time complexity. Algorithms are used for classification, based on the concept of SVM, and for finding the reliability of disorder occurrence.

1. INTRODUCTION

Artificial intelligence is the branch of computer science concerned with making computers behave like humans. Artificial intelligence includes the following areas of specialization:

- Expert systems
- Natural Languages
- Neural Networks
- Robotics [1]

An expert system is computer software that attempts to act like a human expert on a particular subject area. Intelligent systems are often used to advise non-experts in situations where a human expert in unavailable. The basic components of an expert system are: User Interface, Inference Engine and Knowledge Base [2].

In this research a new expert system named Classification Based Target Specific Expert System (CTSES) is proposed.

2. RELATED WORK

Authors exposed the automatic computation system to analyse the cotton leaf spot diseases. Three features, namely color feature variance, shape and texture feature variance, are extracted by PSO [3]. Crops are classified on the foundation of shape, color and texture with SVM, BPN, Fuzzy along with Edge, CMYK features and GA feature selection are combined for training and testing the cotton diseases dataset [4]. Three different color models for extracting the damaged image from cotton leaf images were implemented, namely RGB color model, HSI color model, and YCbCr color model [5].

Authors reported an image-processing based algorithm to extract plant disease symptoms from colored images. The processing algorithm developed starts by converting the RGB image of the diseased plant or leaf, into the H, I3a and I3b color transformations [6]. ESDIABETES was developed to help people monitor and control the blood glucose level [7].

Development environment was proposed that supports the integration of high level knowledge into host projects, data integration from conventional database systems and system's verification, debugging and profiling [8]. A fuzzy expert system framework was proposed which constructs large scale knowledge based system effectively for diabetes [9].

3. CTSES ARCHITECTURE

CTSES served at two levels of functional processes as user and domain expert. Further, it involves development activities that allow end users to build their own decision support system. End users will have provision to use their own set of decision making parameters to build the target-specific decision support system.

Fig. 1 shows the three-tier architecture of CTSES. There are three components named as: Knowledge Base, Inference Module and the User Interface.

3.1 Knowledge Base

The Knowledge base is divided into two parts as dynamic and static. The static part of the knowledge base involves the data

collected from experts as well as data gathered from various other reliable sources. The dynamic part of the knowledge base is formed when the Disorder Database Record (DDR) is created from the static database. The KB of CTSES contains all facts related to cotton crop.



Fig. 1: Three-Tier Architecture of CTSES

3.2 Inference Module

The inference module consists of various other modules which help in the inferencing process. The inferencing module is sub-divided into four parts as follows:

- a) Selector and Insertor Module: In Selector Module, the end user, according to their requirements, selects the parameters such as temperature, humidity etc. known to the best of their knowledge for the better outcome in response to the query. In Insertor Module, the end user provides the information in the form by inputing the values or selecting appropriate option from the list of choices provided. User inserts the values for more appropriate and better results by providing the conditions in which the crop is affected by the disorder causing agent.
- b) Classification Module: The classification module classify and group the diseases which are caused by same agents such as virus, bacteria, fungi etc. The classification module is also based on Support Vector Machines (SVM), as provided by the widely used 'libsvm' implementation. It uses the concept of SVM where number of attributes with numeric data are considered for classification. The mean and standard deviations are calculated to further classify the records.
- c) Disorder Database Generator Module: In this module, the Disorder Database record is created. The dynamic database is created based on the information provided by the user and based on the successful matches with the present knowledge base. The Disorder Database also contains the weight factors associated with each

symptom which may represent the occurrence of particular type of disorder.

d) Refining and Evaluation Module: Once the DDR is created, the weights associated with each symptom is considered and calculations are done based on fuzzy logic to provide some score and associate it with each disorder. The refining and evaluation module generates a list according to the probability of occurrence of disorder and display it to the user.

3.3 User Interface

Here, the user communicates with the system through a Graphic User Interface (GUI) to provide the query and obtain the results.

4. PROCESS FLOW OF CTSES

The CTSES is designed to provide a user friendly environment where the user can build their own intelligent systems using their own knowledge. Fig. 2 shows process flow diagram of CTSES as follows:

Step 1: The user communicates with the system through the GUI to provide query using selection of parameters to the system.

Step 2: The user communicates with the system through GUI and selects the parameters such as temperature, weather etc. and provides the values for the selected parameters.

Step 3: The data in the knowledge base is now classified and grouped. Diseases caused by same causing agent are grouped together. Further reclassification is done. Knowledge base is classified on the basis of causing agents like bacteria, virus etc. This classification grouped the probable resulted diseases together.



Fig. 2: Process flow diagram of CTSES

Step 4: The classified data is reclassified on the basis of mean and standard deviation of temperature and weather conditions.

Step 5: After reclassification, user has to select the affected region of cotton crop like leaves, stem etc.

Step 6: The According to the region selection, a list of symptoms are produced to user. The membership degree for the selected symptoms are taken as input from user.

Step 7: These symptoms work as facts for the inference engine. According to selected symptoms, Inference Engine reach on a decision.

Step 8: The probable disease is produced with the percentage value of its reliability.

Step 9: The result is displayed to the user using GUI.

5. REASONING OF THE CLASSIFICATION MODULE

The classification is done in CTSES on the feature vector selection. The classification is completed in two phase. In first phase, classification is done on the basis of having same causing agents such as virus, bacteria, fungi etc. In second phase, reclassification is done on the basis of mean and standard deviation.

5.1 Mathematical Description for classification

Let D be a classification dataset with n points in a ddimensional space $D = \{(xi, yi)\}$, with i = 1, 2, ..., n and let there be only two class labels such that yi is either +1 or -1.

A hyperplane h(x) gives a linear discriminant function in d dimensions and splits the original space into two half-spaces:

h(x) = wtx + b

where w is a d-dimensional weight vector and b is a scalar bias. Points on the hyperplane have h(x) = 0, i.e. the hyperplane is defined by all points for which wtx = -b.

If the dataset is linearly separable, a separating hyperplane can be found such that for all points with label -1, h(x) < 0 and for all points labeled +1, h(x) > 0 [10].

Step1: Identify the attributes with the numeric data.

Let us assume temperature (t) and weather (w). Let t=30 and w=50.

Step2: Use the data to find the mean and standard deviation which will help in identifying the class and its range respectively.

$$Mean = (30+50)/2=40$$

Standard Deviation = ((-10)2 + (10)2) / 2 = 10.

Step 3: Use training data for better classification using the svm technique..

5.2 Algorithm for classification

Step 1: Select a random variable (x) for elements of list.

Step 2: Set the number of classes as the nature of state (wi).

Let the number of classes be three, than $w = \{ w1, w2, w3 \}$.

Step 3: Extract feature vector from each class.

Step 4: Distinguish the class based on extracted feature vector.

The proposed research used fuzzy reasoning algorithm for finding the reliability of occurrence of diseases using the algorithm [11].

6. WORKING OF CTSES

For the implementation of CTSES, a user interface is designed and implemented along with knowledge base and inference mechanism. Various classification and refining techniques are used to make this system more efficient and fast. ASP.NET Framework environment with the support of languages like C# is used. The DBMS package used for the creation of database is MySQL.

The working of CTSES is described using the following figs. :

Step 1: User Interface for Selection of parameters and input values



Fig. 3: User Interface for Selection of parameters and input values

In Fig. 3, the output is shown which includes the page which is visible to the user when they run the system. It includes codes where the user can select the parameters and provide the information.

Step 2: Classification of the disorders on the basis of causes.



Fig. 4: Classification of disorders

In Fig. 4, the output is shown after selecting and inserting the values to the system. It includes output where the classification of the data is done on the basis of cause of the disorders.

Step 3: Reclassification and generation of Disorder Database Records

In Fig. 5, the output is shown after further classification. Here the user can view the generated database records and can further proceed to refine the search by selecting the desired affected region of the crop.

AN IMPROVED TARGET SPECIFIC FUZZY INTELLIGENT SYSTEM FOR							
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25-35	MODERATE MODERATE	E LEAVES	BALL SHEDDING	SMALL SPOTS	YELLOW SPOTS	ESCOBILLA	FUNGI
25-35	MODERATE LOW	LEAVES ROOT	YELLOW BROWN LEAVES	WILT	ROOT DECAY	COTTON ROOT ROT	FUNGI
25-35	MODERATE HIGH	LEAVES	STUNTED	UPWARD CURL	SWOLLEN VEINS	LEAF CURL	VIRUS
25-35	MODERATE HIGH	LEAVES	ENATIONS	STUNTED	DOWNWARD CURL	LEAF CRUMPLE	VIRUS
25-35	MODERATE HIGH	LEAVES	STUNTED	ENATIONS	LEAVES CURL	TERMINAL	VIRUS
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Fig. 5: Reclassification and generation of Disorder Database Records

Step 4: Refined results with the user capability of selecting the prominent symptoms and their respective membership degree

In Fig. 6, the output is shown after further selecting the affected region of crop to narrow the search results. Here the user can view the generated database records and can further proceed to select the symptoms prominent to the crops and their respective membership degree.

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	25-35	moderate	low	leaves	root	yellow	brown leaves	wit	root decay	Cotton root rot	fungi
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Fig. 6: Refined results with user symptom selection interface

Step 5: Evaluation and final result:

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Fig. 7: Evaluation and final result

In Fig. 7, the output is shown which includes the page which is visible to the user after evaluation of the result based on the information provided.

7. RESULT AND DISCUSSION

Table 1 show the percentage of diseases disorder when different temperature and weather conditions are tested for cotton crops.

Table1: List of disorders and percentage of occurrence(temperature and weather conditions are constant) for
cotton crop.

Disorder	Percentage of Disorder Occurrence (%)
Fusarium Wilt	50.10
Seedling Disease	73.96
Cotton root rot	84.79
Leaf curl	63.82
Leaf crumple	85.54

Table 2: List of temperature range and percentage of disorder caused by fungi (weather conditions are constant) for cotton crop

Temperature (°C)	Percentage of Disorder caused by Fungi (%)
15-25	80
26-35	60
Above 35	50

A list of five probable diseases is produced when temperature at 300C and weather at 'moderate' condition is kept. Table 1 show the reliability of five diseases which are inferred by CTSES. The outcomes are based on symptoms selected by user, their weight factor and membership degree.



Graph 1: Disorder Occurrence percentage, temperature = 30^oC and weather condition = moderate

A list of three temperature ranges is shown when weather at 'wet' condition is kept. Table 2 show the percentage of diseases which are caused by fungi when different temperature ranges are considered for cotton crop.

Graph 1 shows the higher percentage of 'Leaf Crumple' disease (85.54%) shows that the symptoms selected by user has higher membership degree for this particular disease and lower percentage for 'Fusarium Wilt' disease (50.1%) when temperature at 30° C and weather at 'moderate' condition.



Graph 2: Fungi causing diseases percentage, weather condition = wet.

Graph 2 shows the percentage of Fungi causing diseases when weather at 'wet' condition. It can be inferred that the fungi causing diseases are more when temperature conditions are low and decreases with increase in temperature. Hence, cotton crop is more prone to fungal disease at low temperature range.

8. CASE STUDY: COTTON CROP

The case-study of cotton crop with following steps are taken to diagnose the Cotton Root Rot disease.

Temperature Range = $25^{\circ} - 35^{\circ}C$

Weather Condition = Moderate.

Step 1: Select symptom from list of disorder.

 $A_0 = (x_1, x_2, x_3, \dots, x_n)$ where A includes all symptoms.

Let $A_0 = (1,1,0)$

Step 2: Generate Membership degree for selected symptoms (infected plants / total plants)

 $B_0 = (A(x1), A(x2), \dots, A(xn))$

where A(xi) = f(xi) = times(xi) / T

Let $B_0 = (0.8, 0.9, 0.4)$

Step3: Use weight set for selected diseases.

 $W = (w1, w2, w3, \dots, wn)$

Let weight = (0.7, 0.9, 0.2)

Step 4: Calculate weighted Euclidean Distance.

 $d(A_0, B_0) = (\sum_{i=1}^{n} to n Wi (1 - A(xi))2) 1/2$

weighted Euclidean Distance: $d(A_0, B_0) = 0.1923$

Step 5: Calculate relative weighted Euclidean Distance.

 $y(A_0, B_0) = d(A0, B0) / (\sum_{i=1}^{i=1} to n W_i) 1/2$

Relative weighted Euclidean distance: $y(A_0, B_0) = 0.1520$

Step 6: Reliability

 $C(A_0, B_0) = 1 - y(A_0, B_0) = 0.8479$

9. CONCLUSION AND FUTURE WORK

A Classification Based Target Specific Expert System helps farmers to increase the productivity of cotton crops by providing the information about the diseases and its treatment.

The classification module helps the system to find results faster from large database by reducing the number of searches and decreasing time complexity. Algorithms are used for classification based on the concept of SVM and for finding the reliability of disorder occurrence. Various test cases are generated which shows the efficiency of system is better than traditional systems.

The future work includes the training mechanism which can be used to train the data and also provides the feedback to the existing knowledge base. Any additional information from the end user can be considered for the feedback mechanism and can be used to update the knowledge base. The system can be released on different web portals, internet, intranet, or as mobile apps.

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