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Intelligent diagnosis of diseases in plants using a hybrid Multi-Criteria decision making technique

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ABSTRACT

This paper describes an Expert System that can intelligently diagnose diseases in plants. The system is dialog-based and uses a Multi-Criteria Decision Making technique that is a hybrid of Analytic Hierarchy Process and Sensitive Simple Additive Weighting. The paper describes an approach for disease modeling that uses a set of characteristics which are weighted for each disease using two types of weights: Relative Weights and Scales. The diagnostic process involves calculating the utility value for each disease based on the utility values of its characteristics. Experimental results show an accuracy of over 95%. The system implemented is called AgriDiagnose and it consists of a web-based pathology tool to model the diseases and a mobile app for farmers to interact with the system for disease diagnosis in the field.

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1. Introduction

Diseases have the potential to destroy large numbers of crops and can result in significant losses and food shortages if not detected and controlled in time. For example, the Papaya Ringspot virus affected the country of St. Kitts and destroyed about 90% of that country's production (Chin et al., 2007). Many developing countries organize plant clinics for farmers at which farmers can be educated about various pests and diseases and where plant Pathologists can diagnose diseases from samples that farmers bring to the clinic. This is often in addition to visits to the farms by Agriculture Extension Officers. Much work has also been done in trying to automate diagnosis (Barbedo, 2016; Gonzalez-Andujar et al., 2006; Mansingh et al., 2007). These Artificial Intelligence systems generally either apply image processing techniques to images of diseased plants or use a data entry dialog system to attempt a diagnosis.

In this paper, we present a dialog based system for diagnosis of plant diseases. The system uses a multi-criteria decision making technique that is a hybrid of Analytic Hierarchy Process (AHP) (Saaty, 1977) and Sensitive- Simple Additive Weighting (S-SAW) (Goodridge, 2016) to dynamically put forward questions to the farmers in an optimal way and to reason through their responses returning a diagnosis. A major contribution of the paper is the approach presented for modeling diseases using a consistent set of characteristics (criteria). The AHP is used for determining weights of these characteristics for all diseases in the system. The diagnosis process uses S-SAW for sensitivity analysis. The S-SAW is an extension of the popular SAW method (Hwang and Yoon, 1981) which allows the decision maker to define an objective function which governs the optimization goals of each criterion. This is used in calculating the utility value of each characteristic.

This technique was implemented in a system called AgriDiagnose, a system that consists of a back-end, web-based pathology tool and a front-end mobile app for farmers. The results obtained from experimentation gives a 95.9% accuracy for diagnosing the correct disease and a 100% sensitivity result that the system returns a positive result when the plant is indeed diseased.

The rest of the paper is organized in this manner. In Section 2, we review some of the approaches taken in the literature to intelligent diagnosis of plant diseases. In Section 3, we describe the disease modeling that is configured in the Pathology tool and in Section 4, we describe the diagnostic process. We trace one case study throughout these two sections so that the reader can follow the process with data. In Section 5, we reveal the results obtained from our simulation exercises and introduce four metrics for measuring these results. We conclude in Section 6.

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2. Background and related work

Farmers would benefit from a diagnostic process that could intelligently act as a human pathologist. This diagnostic process would take the same inputs that farmers typically provide to a pathologist, process them and return real-time diagnoses. Many of the expert systems that have been developed receive input data from images and use image processing methods or through data entry by users through a user interface. Barbedo (2016) provides a comprehensive survey of expert systems applied to plant disease diagnosis.

Here we review a select sample of the different artificial intelligence (AI) methods that have been applied by researchers and illustrated in Table 1.

A system that uses Fuzzy Logic together with image processing was developed to perform disease identification in the pomegranate crop (Sannakki et al., 2013). The application used images of the leaves of the plant taken by farmers, extracted the features of these leaves and processed them. Using Fuzzy Logic, they were then classified as either diseased or healthy and if found to be diseased, they were graded using the application's Fuzzy Inference System. Bashish et al. (2011) used image processing along with a neural network classifier to detect diseases in leaves. K-means clustering was performed on the images to find actual segments of the leaves followed by feature extraction of the diseased part of the leaves. Statistical analysis was performed to choose the best feature in the leaves, and finally, classification was executed using a neural network classifier.

Dewanto and Lukas (2014) developed an expert system for diagnosing pests and diseases in some of the main fruit plants grown in Indonesia. Their system used a rule-based dialog method. To cater for levels of uncertainty, rules had confidence variables applied to them. The inference engine used the backward chaining method as its goal-driven control technique. JAPIEST was another expert system developed by researchers to diagnose diseases and pests in tomatoes grown in hydroponic greenhouses (Lopez-Morales et al., 2008). This system also relied on rule-based reasoning. Knowledge obtained from experts was represented in the form of dependency networks.

Fuzzy Expert Systems, instead of using Boolean type logic, apply a collection of fuzzy logic's membership functions and rules to return a conclusion. A Fuzzy Expert System was developed to diagnose disease in the Chickpea plant (Dubey et al. 2014). Kolhe et al. (2011) presented a Fuzzy Expert System for diagnosis of diseases in Soybean in India. It applied a new approach to rule-based fuzzy logic called rule promotion using both forward and backward chaining.

Bayesian Networks have been used to create a plant disease diagnosis system that both actively and dynamically performs the diagnostic process (Zhu et al., 2013). The authors applied a concept called 'active symptom selection' which uses only the symptoms that are relevant for the active diagnosis at a point in time. The system used the Bayesian network together with a Markov Blanket to determine the symptoms most relevant in the diagnostic process.

Camargo et al. use multi-class Support Vector Machines to classify a crop disorder based on attribute values supplied by the user (Camargo et al., 2012). For computing a diagnosis, the attribute data is mapped to a feature vector and the mc-SVM prediction model is applied to the feature vector resulting in a probability with which the feature vector belongs to the class.

Our approach combines several different multi-criteria decision making techniques to dynamically put forward questions to the farmers and reason through their responses returning a diagnosis for the suspected disease.

3. Disease modeling

In the approach presented in this paper, all information about each disease is brought together using the concept of a disease model where a model fundamentally contains all the characteristics of one disease. Each model consists of many characteristics where a characteristic in the simplest terms describes something about a model, for example, spot color. Characteristics may be grouped into categories/types as detailed in Table 2.

Therefore, for each disease there exists a Disease Model d_i that belongs to the set containing all models D (Eq. (1)).

$$\boldsymbol{D} = \{\boldsymbol{d_1}, \boldsymbol{d_2}, \boldsymbol{d_3}, \ldots, \boldsymbol{d_n}\} \tag{1}$$

All characteristics belong to a pre-defined set C which holds all characteristics that any member of D can contain. Having this fixed set of characteristics ensures that there would be one standard, consistent set of vocabulary that would be used during the diagnostic process, avoiding any confusion in future and reducing the likelihood that there would be multiple versions or values of characteristics that essentially have the same meaning. Therefore, letting m be the total number of distinct characteristics we have (Eq. (2)):

$$\boldsymbol{C} = \{\boldsymbol{c_1}, \boldsymbol{c_2}, \boldsymbol{c_3}, \ldots \boldsymbol{c_m}\} \tag{2}$$

Models have a many-to-many relationship with characteristics which means that a disease model can contain one or more characteristics and vice versa (Fig. 1). This relationship is essential in the diagnosis process as it relies on the fact that a characteristic is associated with more than one model.

There is one somewhat special type of disease model that is also needed. This is a model that represents a healthy plant. What distinguishes these models from the others is that they have characteristics linked to them that relate to a healthy plant. For each plant type that exists, there will be one instance of this model. This

Table 1
Pest and disease diagnostic systems.

Analytical technique	Plant	Pest/disease	Input	Comments
Fuzzy logic Sannakki et al. (2013)	Pomegranate	Bacterial blight, anthracnose, wilt complex	Images	Diagnosis limited to one plant
Artificial neural network Al Bashish et al. (2011)	Plants (general)	Leaf diseases		Only 5 types of leaf disease diagnosed
Fuzzy expert system Dubey et al. (2014)	Chickpea	Pests and diseases *(limited to plants observed)*	Text	Limited to the chickpea plant
Expert system Dewanto and Lukas (2014)	Fruit plants			Expert system trained by programmers
Bayesian networks with incremental learning Zhu et al. (2013)	Food crops			Bayesian networks used
Support vector machines Camargo et al. (2012)	Any food crop	Pest disorders		Multi-class SVM using disease attribute vector
AgriDiagnose expert decision making system; AHP and S-SAW	Any food crop	Unlimited		Easily extendable, limited only by the data that has been entered by Plant Pathologists

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