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Hybrid learning of fuzzy cognitive maps for sugarcane yield classification

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ABSTRACT

Sugarcane is one of India's most important renewable commercial crops. The sugarcane cultivation and sugar industry plays a vital role towards socio-economic development in the rural areas by creating higher income and employment opportunities. Early detection and management of problems associated with sugarcane yield indicators enables the decision makers and planners to decide import or export policies. In this work, a hybrid approach using fuzzy cognitive map (FCM) learning algorithms for sugarcane yield classification is proposed, combining the key aspects of Data Driven Nonlinear Hebbian Learning (DDNHL) algorithm and Genetic Algorithm (GA) called FCM-DDNHL-GA. The FCM model developed for the proposed study includes various soil and climate parameters which influence the precision agriculture application of sugarcane yield prediction. The classification accuracies and inference capabilities of the hybrid learning algorithm of FCMs are analyzed and compared with some well-known machine learning algorithms for sugarcane yield monitoring application. Experimental results show the superiority of the hybrid learning approach by providing significantly higher classification accuracy.

1. Introduction

India is one among the largest producers, consumers and trading of agricultural products. The abundance of crops has long been paid much attention by society and government. Sugarcane (*Saccharum* sp.) is one of the most important traditional and commercial crops of industrial importance in the world because of its strategic position and immense uses in the daily life. In recent years, global interest in sugarcane has increased worldwide due to its economic impact on sustainable energy production. Sugarcane provides raw material for the second largest agro-based industry next to textile and is the base for all major sweeteners produced in the country. The unprocessed sugarcane is used as human food and animal feed. Brazil, India and Cuba are the leading countries in sugarcane production, producing over half of the total sugarcane production in the world (Girei and Giroh, 2012). Sugarcane cultivation remains an important part of the socio-economic development in the rural areas by generating higher income and employment opportunities to more than half a million people, either skilled or partly skilled workers (http://www.iisr.nic.in/iisrvisiion2030.pdf). In India, the sugarcane planting season in subtropical regions is September to October and February to March, whereas in tropical regions it is January to February, June to August and October to November. Apart from this, in some states like Karnataka and Tamil Nadu, sugarcane planting continues throughout the year except few months. The climatic and soil conditions as well as other facilities like irrigation have facilitated increased sugarcane cultivation in Tamil Nadu.

The production of sugarcane and prediction of its yield have direct impact on national and international economies and play an important role in the food management (Hayes and Decker, 1996). Assessment of particularly decreased production caused by a natural disaster, such as pest infestation or drought, can be critical for countries where the economy is greatly dependent on the crop harvest. Early detection and management of problems associated with crop yield indicators can help increase in yield and subsequent profit. Early prediction of crop yield to the global and regional scales offers useful information to policy planners. The crop yield information at the field level also helps the farmers to make quick decisions on upcoming circumstances, such as the choice of alternative crops or whether to abandon a crop at an early stage of growth. Barnett and Thompson (1982) used meteorological models based on temperature and precipitation for forecasting wheat yield. Parthasarathy et al. (1988) and Ramakrishna et al. (2003) have developed forecast equations using regression models

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for Indian food grain production with the help of monsoon rainfall and soil indices. First-order Markov Chain model was developed for forecasting sugarcane yield by using the growth indices of the biometrical characters (Ramasubramanian and Jain, 1999). The proposed model outperforms compared to the regression model. Remote sensing and Global Positioning Systems (GPS) can be used to assess spatial variability in crop yield (Taylor et al., 1997). The neural computing approach has been used to estimate corn and soya bean yield of the Lowa state of US (Jedendra and Kavitha, 2008) and has shown a better performance when compared to piecewise linear regression method.

Deressa et al. (2005) applied a Richardian cross section regression model and proved that the sugarcane productivity is highly sensitive to climate change. Ramulu (1996) employed a Cobb–Douglas production function to analyze the impact of rainfall and other socio-economic factors on sugarcane production in Andhra Pradesh. The climate variables like minimum and maximum temperature are not considered in this study. Ranuzzi and Srivastava (2012) justified that the more fertilizer application has greater impact on climate change and environmental damage. The authors Kumar and Sharma (2014) employed simple linear regression model, Richardian regression model and Cobb Douglas production to assess the impact of climate and socio-economic factors on sugarcane productivity. It is concluded that the increase in the average minimum and maximum temperature as well as the average rainfall has significant impact on sugarcane production. Additional irrigation facilitates adverse effect on climate change and increasing fertilizers application would be harmful. Suresh and Krishna Priya (2009) developed a sugarcane yield forecast model for Coimbatore district, which successfully estimates the pre-harvests yield in advance before the actual harvest.

In precision agriculture, subsequent attempts have been made by applying artificial intelligence principles and soft computing techniques for spatial analysis and crop management (Drummond et al., 2003; Huang et al., 2010). Specifically, ANN analysis has been applied in precision agriculture for spatial analysis and crop management (Drummond et al., 2003; Irmak et al., 2006). The ANNs have been combined with other artificial intelligence techniques or other statistical methods to benefit from the advantages of ANN modeling, and avoid some of their limitations such as the need for large amounts of data for training. In addition, machine learning algorithms have been applied for cotton yield classification (Jamuna et al., 2010) as well as rule mining algorithms have been implemented for classification in agriculture (Khan and Singh, 2014). Soft computing techniques and their applications in agricultural and biological engineering are summarized by Huang et al. (2010).

An alternative soft computing technique, the fuzzy cognitive mapping (FCM), which has been previously used for yield prediction, is investigated in our case study for sugarcane yield classification. FCMs constitute an attractive knowledge based modeling methodology, depicting a system in a form that corresponds closely to the way humans perceive it. An FCM combines the properties of fuzzy logic and neural networks to represent the dynamics of any complex system (Papageorgiou, 2014). Due to their ease to construct and use, their flexibility and adaptation in applying to any problem domain, support on uncertain knowledge, ability to execute fast, relatively simple and comprehensible modeling philosophy which is very close to human reasoning, they have the capability to handle the complex issues efficiently in different domains (Papageorgiou, 2013). Therefore, FCM has become popular and found large applicability in many diverse application areas including medical diagnosis (Papageorgiou et al., 2008, 2015; Subramanian et al., 2015), modeling of plant control (Gotoh et al., 1989), analysis of electrical circuits (Styblinski and Meyer, 1991), fault managing in networks (Ndousse and Okuda, 1996), modeling of political affairs in South Africa (Khan and Quaddus, 2004), coconut yield management (Jayashree et al., 2015), etc. In addition, FCM has been applied by Papageorgiou et al. (2010, 2011, 2013) in precision agriculture to model the relationship between the factors influencing the cotton yield and analyze their cause – effect relationships since it has been already proved as a successful modeling methodology for many real life applications. Papagerorgiou et al. used FCM model to predict cotton yield (2009, 2010, 2011) and apple yield (2013) in central Greece. It was proved that FCM technique enhanced by its Hebb-based learning capabilities outperformed when compared to other machine learning algorithms for precision agriculture applications. As such, different FCM structures and learning schemes have been proposed in the relevant literature, while numerous studies report their use in many contexts with highly successful modeling results (Papageorgiou, 2014). This type of modeling, simulation and inference offers a new form of decision support through simulation analysis and forecasting. The number and diversity of already reported applications motivated the authors of this paper to apply the FCMs for sugarcane yield classification by considering detailed soil and climate profile. The main objectives of the proposed work are to study the influence of soil and climate parameters on the productivity of sugarcane and to classify the sugarcane yield using different FCM learning approaches. The main contribution of this research study is the proposition of a new hybrid learning approach for FCMs, which seems more accurate and efficient than the previous learning approaches applied in FCMs for classification tasks in yield management.

The remainder of this paper is organized as follows. In Section 2, an overview of FCM and various algorithms for FCM learning are presented. Section 3 describes the FCM construction process of the proposed study. Section 4 presents the hybrid learning algorithm for FCMs applied for yield classification. In Section 5, the experimental results were presented and discussed. Finally, Section 6 outlines the conclusion and future outlook.

2. Background of fuzzy cognitive maps

FCMs constitute an attractive knowledge based modeling methodology, depicting a system in a form that corresponds closely to the way humans perceive it. FCM can be represented as a directed graph consist of a set of nodes, which basically correspond to concepts bearing different states of activation depending on the knowledge they represent, and the edges correspond to the causal effects that each source node exercises on the receiving concept expressed through weights. Weights assigned for edges can take fuzzy values in the interval [−1, 1]. Construction of FCM relies on single or group of human experts (Papageorgiou et al., 2009) who have good domain knowledge and experience on the system. They determine the type and the number of concepts as well as the initial weights. A sample FCM shown in Fig. 1 illustrates six concepts

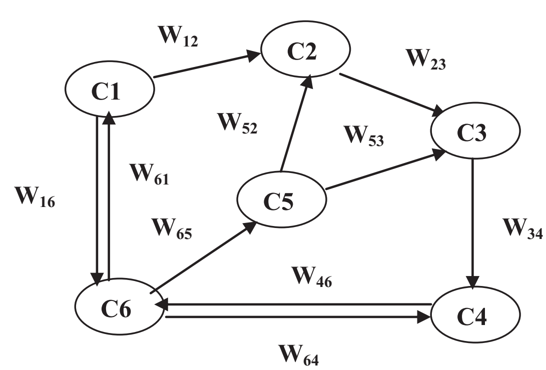

Fig. 1. A sample fuzzy cognitive map with 6 concepts.