Towards a Semantically Enriched Computational Intelligence (SECI) Framework for Smart Farming

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Abstract. This paper advocates the use of Semantically Enriched Computational Intelligence (SECI) for managing the complex tasks of smart farming. Specifically, it proposes ontology-based Fuzzy Logic for dealing with inherent imprecisions and vagueness in the domain of smart farming. The paper highlights various characteristics of SECI that make it a suitable computational technique for smart farming. It also discusses a few aspects out of the huge number of possible applications in smart farming that we are planning to implement with the help of SECI. Further, it shares in detail the implementation and some preliminary results obtained by applying SECI to one specific aspect of smart farming.

Keywords: Smart farming · SECI · Intelligent agriculture · Knowledge-based agriculture

1 Introduction

Smart Farming (SF) is based on the idea of harnessing Information and Communication Technologies (ICT) for improving the efficiency, productivity, and efficacy of agricultural operations. SF has several aspects with the most important being smart sensing, smart planning/analysis, and smart control. Smart sensing employs advanced sensing technologies to obtain accurate and up-to-date information on soil and climatic conditions in a crop field. Smart planning/analysis uses data analytic and predictive tools for making optimal decisions depending on actual data obtained from the field. Smart control refers to reconfiguration of smart sensing devices on the field depending on real time data. A number of technologies act as enablers of SF including Internet of Things (IoT), Big Data, robots, drones, and Cloud Computing among others.

Computational Intelligence (CI) deals with representation and reasoning schemes for domains where accurate models are not feasible. Examples of CI techniques are Artificial Neural Networks (ANN), Fuzzy Logic (FL), Case Based Reasoning (CBR) and Genetic Algorithms (GA). These techniques aim at making optimal

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decisions in face of problems that are not precisely defined and where the search space is so large that any optimal decision is as good as the best but elusive decision. Agriculture is one such field where quantitative modeling is not possible due to the huge number of parameters related to climate, temperature, soil, humidity, crop appearance etc. There are complex interactions between the parameters which are difficult for analytical reasoning. Many of the parameters are qualitative in nature e.g. crop color, pest size etc. Due to this, the parameters do not take on a crisp definite value in a decision situation. For example, not all leaves that are brown are diseased, but sometimes this color maybe a warning sign of disease. Moreover, as SF becomes available at scale, the sheer number of parameters for decision-making becomes non-trivial. Managing SF with large number of parameters can benefit a lot from linguistic reasoning techniques offered by CI. Data representation in qualitative, relative terms also makes sense because the data in real time is also continuously changing due to the dynamic nature of agriculture domain.

Agricultural scientists and experts, through years of experience, have accumulated reserves of heuristic knowledge that has shown to get results in face of vague and incomplete data. This knowledge ought to be part of any smart solution, but is difficult to model mathematically. A knowledge-base and computable ontology is the most appropriate tool to encapsulate such semantically rich, qualitative knowledge.

This paper proposes the novel idea of using a specialized branch of CI, namely Fuzzy Logic (FL) in combination with semantically representative ontology for smart farm management. FL comes in as a strong technique because we need to make inferentially strong decisions in presence of approximate data and relying on expert knowledge. This expert knowledge gets its expression in the form of a semantic ontology. The link between expert knowledge and inference framework is established by defining computable mappings between semantic terminology and computable features in the domain.

This paper has three primary contributions:

- It proposes a novel Fuzzy Logic based SECI framework for smart farming.
- It discusses attributes of SECI that make it applicable to various dimensions of smart farming.
- It describes three possible applications of SECI in smart farming that we are planning to implement and explains one of these application in detail.

Rest of this paper is organized as follows. Section 2 is a brief introduction to various CI and semantics technologies. Section 3 is the literature review. Section 4 gives some possible applications of SECI in smart farming. Section 5 covers the application that we are currently working on. Section 6 presents the experimental setup and results. Finally, Sect. 7 concludes the paper with options for future work.

2 Computational Intelligence and Semantic Technologies

Here we give a brief introduction to the CI and Semantic technologies directly relevant to our work:

2.1 Fuzzy Sets

A fuzzy set [14] allows for graded membership of its elements. A fuzzy set A is defined as: $A = \{\mu_A(x)|x \in X\}$ where $\mu_A(x)$ is the membership function for any $x \in X$, X is the domain of discourse and $\mu_A(x) : X \rightarrow [0, 1]$. The essential characteristic of Fuzzy Sets is the absence of sharp boundaries between members and non-members of the set which is not possible in classical set theory.

2.2 Fuzzy Logic (FL) and Fuzzy Rule Based Systems (FRBS)

Fuzzy Logic is an extension of classic Boolean logic with provision for graded truth values. FL is used to make inference where exact modeling of the domain is not possible due to imperfect knowledge or imperfect measurement of domain parameters. It allows to reason with qualitative and approximate data by making use of linguistic variables and approximate reasoning. Linguistic variables employ fuzzy sets to represent linguistic terms like hot, cold, humid etc. An FRBS uses linguistic variables belonging to the domain of discourse in the form of fuzzy if-then rules to make inferences. A typical fuzzy rule looks like:

$$if\, \langle fuzzy\, proposition\, with\, linguistic\, variables \rangle\, then\, \left\langle \begin{array}{c} fuzzy\, proposition \\ with\, linguistic\, variables \end{array} \right\rangle$$

During fuzzy inference the fuzzified input is provided to all rules in the FRBS. As a consequence, various rule “fire” up to various degrees depending on the degree to which their antecedents match the input fuzzy data. The output from all the fired rules is aggregated using aggregation operators to obtain the final output, which may then be defuzzified using various defuzzification operators.

2.3 Ontologies

An ontology in Computer Science is a tool for expressing knowledge about a concept or a domain. Ontologies provide a convenient formalism for expressing concepts of the domain and their inter-relationships. They are a powerful tool for creating knowledge based systems.

3 Literature Review

Smart Farming is increasingly gaining importance as a research area. Several papers have discussed the application of CI in agriculture. Here we are discussing only the representative ones according to the approach used. We would like to mention that to the best of our knowledge no paper has discussed the use SECI as an integration of FL and semantics so far.

Many papers describe approaches using computationally intensive techniques relying image data. For instance, in [1] a series of deep convolutional neural networks (CNN) is used to estimate disease severity from plant images. Likewise, in [6] CNN is used to classify disease types from leaf images. The deep learning systems are reliant on a large set of annotated images for its learning and tuning. There is no feature engineering, so the system results are difficult to interpret.

In [2] a fitness function based metaheuristic approach is used to adjust the amount of pest control spray based on predicting the weather conditions impacting deposition.

Neural Networks as a CI technique have been used in a number of smart farming use cases including yield prediction [3] and site specific herbicide management (SSHM) [4]. The black box nature of neural networks however precludes their use as expert knowledge representation.

In [5] the authors present a decision-making framework for aquaculture sites using Case Based Reasoning (CBR). The system utilizes sensor based data to make semantic inferences about conditions and operations related to fish farming.

Flourish [7] is a European Union (EU) project that uses CI in the form of decision trees to coordinate smart farming actions between Unmanned Air Vehicle (UAV) fitted sensors and ground based Unmanned Ground Vehicle (UGV) mounted actuators.

4 Possible Applications of SECI in Smart Farming

Here we are discussing various applications of SECI in smart farming that we are exploring at present.

4.1 SECI in Smart Sensing and Monitoring

Smart sensing and monitoring ensures that the crop is always under surveillance and any change in field parameters is effectively responded to. Natural conditions for various hazardous situations are not precisely defined. For instance, different stages of a foliar disease may show multiple symptoms on different plants. The color and distribution of disease spots may be similar across different pathologies. Since a clear demarcation of deciding parameters and their values is not possible, CI techniques can help in establishing frameworks for representation of seemingly disparate data. A number of CI techniques have in fact been employed for smart sensing of agriculture, e.g. [10]. These frameworks can be further strengthened by integrating with semantic knowledge about the specific application domain. Work is being done on agricultural ontologies e.g. AGROVOC by Food and Agriculture Organization (FAO) [11] and GRIN ontology by US Department of Agriculture (USDA) [12]. However, work is needed to integrate these ontologies/thesauri with computable frameworks.

4.2 SECI in Smart Planning/Analysis

This aspect is concerned with setting objectives for quantity, quality, and timing etc. of farm inputs. It is also concerned with measuring actual behavior against planned one, and initiating appropriate interventions if needed. An SECI based farm manager can maintain objectives, as well as rules regarding control adaptation in case of divergences between anticipated and observed conditions. Beyond the production, SECI can also be used to maximize marketing profits from crop [13]. We anticipate semantically enriched Fuzzy Logic based smart planners for optimal balancing of all resources against performance objectives.

4.3 SECI in Smart Control

Smart Farming is increasingly reliant on large amounts of data from disparate sources. Sudden changes in weather conditions or disease alerts demand intelligent and agile adaptation on part of farm control [9]. SECI can be used effectively for rapid reconfiguration of smart devices based on agile composition and analysis of real time data. We anticipate the use of SECI techniques in representing context-sensitive response to such changes in operational conditions. Since a lot of decision parameters may be involved requiring different responses in different contexts it will be efficient to coalesce seemingly separate but logically similar decision boundaries to economize on computational resource for control and management decisions.

5 SECI in Smart Sensing and Monitoring

Smart sensing and monitoring ensures that the farm conditions are properly monitored to avoid any hazard to crop, e.g. to protect against pest and pathogen attacks. Crop diseases are a major reason for agricultural under-productivity, especially in under-developed countries where knowledge barriers further hinder the framers from timely and accurate detection of disease. Accurate disease detection is crucial for correct management action on part of the farmer. Disease detection and classification however is a complicated challenge due to non-specificity of disease symptoms. It is known that many symptoms are common to multiple diseases. Likewise, a single disease may exhibit multiple variations of symptoms in various cases. Human experts do not face great difficulty in identifying the diseases if visiting the fields; however, the presence of an expert on field is not always possible. We are developing an SECI based disease classification framework where which can replace the human expert for disease classification in-situ. The framework works on cheap sensor-based images of the crop parts to intelligently classify the disease. Due to space constraints, we are describing here only part of the system that identifies leaf diseases. The framework is built around two primary parts: (1) an ontology of visually perceptible (phenotype) features used by experts for diagnosing a disease (Fig. 1) and (2) a classifier that maps the computable representations of ontology features to disease (Fig. 2).

The purpose of ontology is to map sensor based image features to the features employed by experts in identifying diseases. As shown in Fig. 1 the phenotype ontology is divided into three levels; each disease at the top level is expressed as a pattern of phenotype attributes at the intermediate or semantic level. We divide these phenotype attributes into categories as shown in Table 1.

At the lowest level of ontology are sensor generated features that pass through various Digital Image Processing (DIP) procedures (not discussed here). As shown in Table 2 these features are quantitative and numeric by nature e.g. intensity, hue, entropy etc. The innovative aspect about our approach is how we map these features to

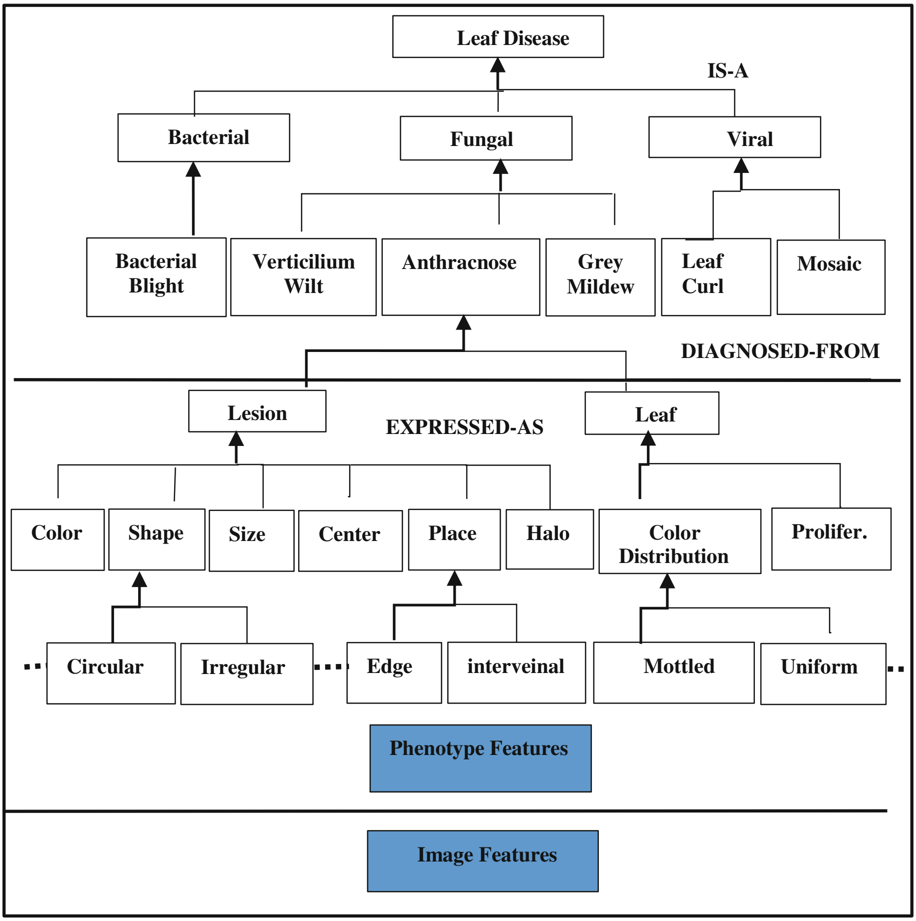


Fig. 1. Partial structure of phenotype ontology

knowledge-based semantic features in the disease ontology. At the next higher level lies the phenotype layer which represents semantic description of disease as understood by the experts. The joint contribution of phenotype expressions leads to inference of a specific disease as expressed by top layer in the ontology.

The classifier takes as input a collection of leaf lesions detected through DIP techniques. First the lesion extraction module executes, giving as output all potential candidates or disease lesions. An image is represented as $x = \{v_1, v_2, v_3, \ldots, v_N\}$ where N is the number of potential lesions detected. For disease classification, each potential lesion is represented by a feature vector $v_i = \{f_1, f_2, f_3, \ldots, f_M\}$ where $i = 1, 2, \ldots, N$.

We model the lesion classes using a proposed hybrid of state of the art classifiers including Logistic Regression Model and Fuzzy Rule Based classifier. First, the image features are mapped to semantic categories using a Multinomial regression model. The

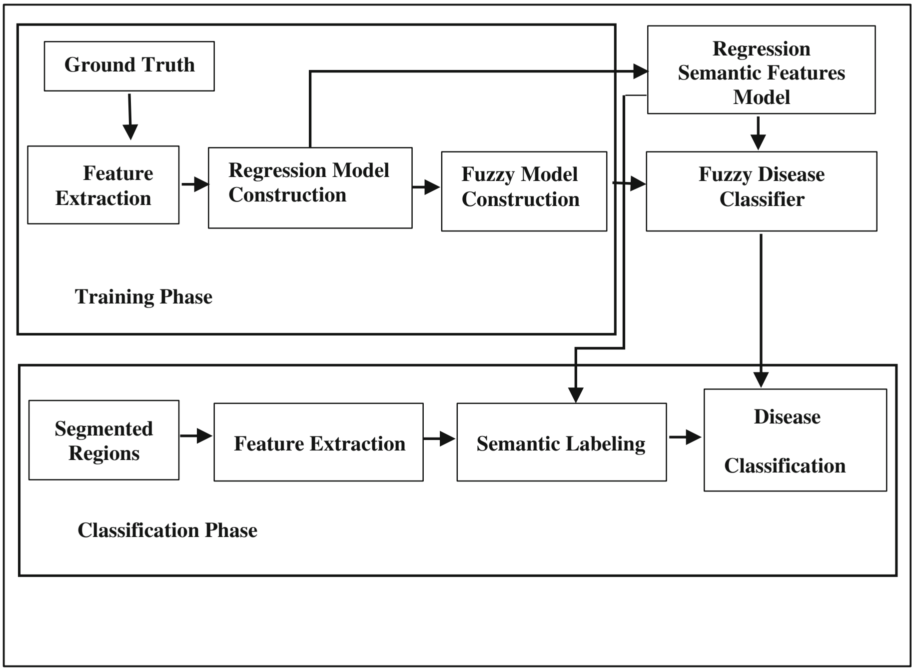


Fig. 2. Classifier architecture

Table 1. Semantic features for disease identification

Category	Phenotype	Possible values
Lesion	Color	{Yellow, green, brown, black, gray, white, purple}
	Size	{Small, medium, large}
	Shape	{Round, polygonal, complex}
	Center structure	{Water-soaked, Sunken, raised}
	Place	{Edge-neighboring, vein-neighboring}
	Halo	{Present, absent}
Leaf	Proliferation	{Dense, sparse}
	Color distribution	{Mottled, Uniform}

output of this model is then used as input to a Fuzzy Rule Based System (FRBS) classifier to decide the disease based on the semantic categories.

We use a Multinomial Logistic Regression (MLR) at first stage of our classification process. Logistic Regression is an extension of ordinary regression with allowance of categorical and ordinal variables as dependent variable. MLR can be used to model dependence on any number of ordinal, continuous, or categorical variables. Since the semantic categories in our framework are categorical in nature, we model them with help of MLR. The MLR model assigns probabilities to each of the semantic classes on

Table 2. Low level features obtained through digital image processing

Category	Phenotype
Color	Global color histogram
	First 4 moments for each channel in HSV color space (mean, standard deviation, skewness, and kurtosis)
	Global color histogram
Shape and size	Centroid, area, perimeter
Statistical	GLCM features (energy, contrast, homogeneity, correlation) at 4 different offsets
Transform	Gabor wavelet responses: mean and standard deviation of Gabor features in 4 orientations and 3 scales

the basis of calculated image features. The probabilities are forwarded to the next FRBS classifier as input.

First of all, the semantic class probability values are fuzzified with help of a fuzzifier on basis of fuzzy membership functions of the form $\mu_F(c)$ such that c is a crisp probability value, F is a fuzzy set and $\mu_F(c) : c \rightarrow [0, 1]$. We use Gaussian membership functions for fuzzification. All fuzzy linguistic variables corresponding to each specific semantic category are processed by an Inference Engine, working on Fuzzy Rule Base, to deduce membership values of all diseases. The rules for disease detection take the form:

$$\begin{gathered} Ru^l : IF\, S_1\, is\, s_1^l\; AND\, S_2\, is\, s_2^l\; AND \ldots S_n\, is\, s_n^l\; THEN \\ D_1\, is\, d_1^l\; AND\, D_2\, is\, d_2^l\; AND \ldots D_m\; is\, d_m^l \end{gathered}$$

where l is the rule index.

There are M rules with K input parameters, each divided into a number of fuzzy terms. Likewise, m output variables are used to express the disease, represented by Gaussian membership functions of the form:

$$\mu_F(c) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{c-\bar{c}}{\sigma}\right)^2}$$

where σ and $\bar{c}$ are standard deviation and mean respectively.

We measure the degree of relevance of each rule to possible diseases using the AND-rule:

$$\mu_{Ru^l}(.) = \mu_{S_1}(.) \cap \mu_{S_2}(.) \ldots \cap \mu_{S_n}(.)$$

where ∩ is a t-norm and (.) denotes the semantic categories. We interpret t-norm operation as min operation, i.e.:

$$\mu_{Ru^l}(.) = \min[\mu_{S_1}(.), \mu_{S_2}(.), \ldots, \mu_{S_n}(.)]$$

We use fuzzy implication operator to determine the firing strength each rule. The implication process yields a fuzzy vector with diseases Di, truncated at $\mu_{Ru^l}(.)$. All rule outputs are aggregated using Mamdani's combination. This yields a fuzzy membership vector: s $= [s_1, s_2, \ldots, s_n]$ in which the entries indicate the degree of membership of each of the n diseases. The membership function for each disease is defuzzified to yield a single membership score for that disease. We use a Center Average (COA) method for defuzzification:

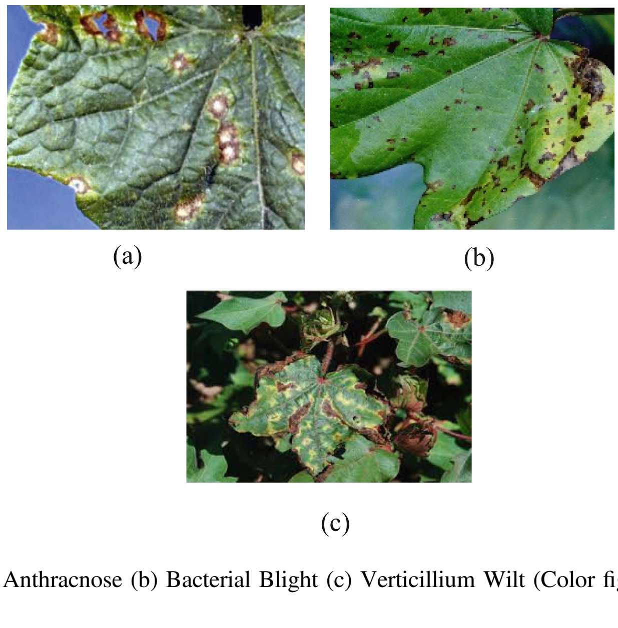
$$o = \frac{\sum_{m=1}^{M} c^m w^m}{\sum_{m=1}^{M} w^m}$$

where o is the output crisp value, M is the number of output fuzzy sets being aggregated, c^m is the center of mth output fuzzy set and w^m is the height of mth output fuzzy set.

The above modeling framework makes it possible to map any combination of image features to corresponding diseases in a manner consistent to expert knowledge.

6 Experimental Setup and Results

The SECI based disease classification system is flexible and can accommodate any number of diseases and features. Currently we have implemented it for three diseases of the cotton leaf: Bacterial Blight, Anthracnose and Verticillium Wilt. Anthracnose is a



(a) (b)

(c)

Fig. 3. (a) Anthracnose (b) Bacterial Blight (c) Verticillium Wilt (Color figure online)

fungal disease that appears as pinkish spots on leaf surface. Areas around veins turn yellow to brown and eventually die out. Bacterial blight starts as scattered small dark green translucent spots on under surface of the leaf. Gradually the spots turn dark brown to black, enlarge and appear on the upper surface as well. The spots also become angular in shape due to veination on the leaf. In case of Verticillium Wilt the leaves develop a characteristic yellow (diffuse or angular) mottle on the edges and around veins. Eventually tissue on the leaf edges may die down and replace the mottle as a dark brown border. Figure 3 shows an example of each disease.

The system is implemented using MATLAB 2015 on an Intel i5 processor. There are 50 images of each kind of disease in the dataset. In Table 3 we present the results of classification using average accuracy over 3-fold cross-validation. It can be seen that the use of more informative features improves accuracy of the system.

Table 3. Experimental results

Feature based accuracy (%)	Accuracy (%)
Color	83
Size	46
Shape	66
Distribution	64
Color, size, shape, and distribution	94

7 Conclusions and Future Work

Smart Farming involves complex data processing and decision making. We have discussed three applications of Semantically Enriched Computational Intelligence (SECI) to various aspects of smart farming. We also discussed one of the applications that we are currently implementing. Experimental results indicate that the idea holds promise and can be explored further. In future, we will explore other applications of SECI in smart farming as discussed in this paper. We will also experiment with other CI approaches in semantically enriched frameworks for agriculture.

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