Intelligent Decision Support System for an Integrated Pest Management in Apple Orchard

T. Padma, Shabir Ahmad Mir and S.P. Shantharajah

Abstract Sizable human population of the world is associated directly or indirectly with the agriculture and natural resources found on the earth and is important to the study of sustainability. Despite of difficulties in practical agriculture, new opportunities have been created by sophisticated technology-driven change to address judicious use and management related problems of resources and thereby improving human wellbeing. In agriculture, Intelligent Decision Support Systems (IDSS) have been used for optimization of number of planning and decision making challenges under variable number constraints based on noisy data. This research describes an IDSS to implement and optimize pest and disease protection decision making processes within temperate regions of India; develops hybrid algorithm using Case Based Reasoning and Database Technology and implement the same using web based client server architecture. The accuracy of decision making process provided by the system has been 90.20% and it can provide significant support to the apple farmers in decision making towards Eco-friendly pest management practices.

Keywords Integrated pest management · Case based reasoning · Insect pest · Data analysis · Behavioral patterns · Computational intelligence

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1 Introduction

In India, apple fruit production has become main horticultural activity in the northern states of Jammu and Kashmir, Himachal Pradesh and Uttarkhand, where this industry is considered as a backbone of economy. An area of 289 thousand hectares are under this fruit with an annual production of about 2890.6 thousand tones [1]. These regions have more than 30 million human population and enormous natural resources, and hence are important to the study of sustainability. Moreover, the demand for fresh fruits especially apple has shown faster growth than other field crops in the recent times [2]. India figures among top ten apple producing countries and its contribution to the overall production is 3% [3–5]. However, the production and quality of apple is poor as compared to that of the developed countries because of several factors including insect and diseases, which cause great loss to the apple growers annually [6–9]. In order to minimize this loss, stakeholders of horticulture sector in developing countries like India are implementing different integrated pest and disease prevention programs for various fruits crops including apple. Implementation of these programmes requires complex tactical decisions and integration of information from multiple sources. Integrated Pest Management (IPM) programmes are often formulated without identifying the real needs of farmers and their advisors wherein imprecise and interconnected information is communicated in the form of bulletins and/or advisories. Due to ever-changing weather conditions and integration of information from multiple sources together with complexities associated with the decision process of IPM, the extension systems are successful only when supported with intelligent systems to address complex decision making. This imprecise and uncertain nature of the IPM includes information that is vague, fragmentary, not fully reliable, contradictory, deficient, and overloading; thus affecting quality fruit production of apple besides it is costly, and can be detrimental to the environmental as well. Intelligent system based decision support can improve decision making process by providing timely solution to critical problems, increase productivity and decrease costs under complex environment [10, 11]. It is surprising that computational methods have not been applied for providing better planning and decision making solutions in these regions. Therefore, due to lack of fast, accurate, reliable and weather aware decision support with the extension system, extension bulletins and advisories often becomes ineffective. This imprecise nature of the IPM is effecting quality fruit production of apple in the temperate regions suitable for apple production. Mathematical modeling is inadequate in these cases given imprecise nature of the IPM problem due to the complex, uncertain and stochastic nature of processes to be modeled. Despite of these difficulties, technology driven change in the form of sustainable computational intelligence can create new opportunities to address poor management of apple production resources thereby improve quality of life.

Computational Intelligence (CI) techniques use computational power of computers to integrate, analyze and share large volume of noisy data in real time, using diverse analytical techniques to discover important information suitable for better decision making. CI techniques can move forward farm economics leaps and bounds by transformation of theoretical concept of computational intelligence techniques into practical agriculture. The process has already begun by the development of weather forecasting [12], crop health monitoring [13], detection and classification of plant leaf diseases [14], fruit and grain grading system [15, 16], precision farming [17], crop prediction [18] and estimation of morphological parameters and quality of agricultural products [19] and many others are clear examples of how these techniques can be future endeavor of farming industry. Application of these techniques can reduce severity of disease and pathogens problems in apple orchards while minimizing applications of spraying substances by focusing on life cycles of pathogens and weather conditions, thus boosting the ability of agricultural and environmental conditions to continue support life on earth.

Considering the limited nature of information presented in the pest protection programme; vagaries in environmental and climatic conditions as well as growing resistant behavior of pathogens towards spraying substances, IPM programme could not achieve desired results. Therefore, in order to supplement climatic and pest phonological data to IPM module, computational intelligent DSS have been developed for temperate regions of India to predict likely consequences of presence of insects, pests or disease in the apple orchards. The effort has resulted in adoption of efficient management practices to minimize repetitive sprays, environmental impact and risk of workers as well as cost of spraying.

This research describes an intelligent DSS that was developed to help apple growers within temperate regions of India in decision making about IPM based on the principles of sustainability to enhance the economic viability of apple fruit crop through optimized management of insect, pest and disease protection with reduction in spraying substance usage. A Hybrid computational intelligent algorithm based on Case Based Reasoning (HCBR) and database technology is presented which supports retrieval, reuse and revise IPM knowledge to provide optimal decision support for various spraying substance viz-a-viz disease diagnosis. The algorithm is implemented using web based client-server system, which provide decision making and predictive forecast support related to pathogens and diseases of apple.

2 Background

Food production and demand in some of the countries like India are fragile due to changes in climatic conditions, spread of diseases and constant degradation of farmland. It is very useful to anticipate the threats to sustainability by predicting climatic conditions; spread of disease or pathogens and shrinking farmland size. But the assessment process of these factors is not straight forward using conventional methods. Besides, combined approach of these factors makes this process expensive, time consuming and inadequate due to scarcity of suitable extension staff, difficulty of logistic transport and timely paper report coordination.

On the other hand, IPM is a synergy of diseases and environmental conditions. Diseases cause severe damage to the tree and eventually economic loss to the farmers. Disease diagnosis in earlier stage is desirable. But it needs study of numerous characteristics of plant, environment and behavior of pathogens and diseases, which are not distinguishable in most cases. Besides, identification and presence of disease is prerequisite for its treatment. Therefore, identification and treatment using computational intelligent techniques is a must and it finds great significance in precision disease management.

3 Integrated Pest Management (IPM)

Integrated Pest Management (IPM) is an effective and environmentally sensitive approach towards pest management that uses a combination of commonsense practices. IPM programs use current, comprehensive information on the life cycles of pests and their interaction with the environment. This information is combined with available pest control methods to manage pest damage using most economical means together with the least possible risk to people, property, and the environment.

All insects and other living organisms do not require management. Many of them are injurious while several others are also beneficial. IPM programs monitors and identifies pest infestation precisely, so that appropriate control decisions can be made in colligation with action thresholds. This monitoring and identification process removes the possibility of imprecise application of pesticides and their timing.

Conjugative approach of field monitoring, disease or pest identification, and action thresholds resolves requirement of pest control. Proper management methods are accordingly evaluated and suggested under IPM programs taking into consideration the effectiveness and risk of the method to be used. At first, effective and less risky pest controls like pheromones to disrupt pest mating or mechanical control such as trapping. This may followed by highly targeted control like usage of spraying substances, when monitoring, identifications and action thresholds indicate less risky method as non-effective. Broadcast spraying of non-specific pesticides is the last resort.

4 Computational Intelligence

Due to design of natural and biological algorithmic models for complex problems, artificial intelligent (AI) systems are being developed. CI is a sub-branch of AI or Intelligent systems, which is a fairly new research field with competing definitions. According to [20] it is the branch of science studying problems for which there are no effective computational algorithms. Computational Intelligence techniques mainly focus on *strategy* and *outcome* by putting emphasis on heuristic algorithms such as fuzzy systems, evolutionary computation and neural networks. They are used to address complex real-world problems to which application of mathematical modeling is inadequate due to the complex, uncertain and stochastic nature of processes to be modeled [21]. In essence, CI refers to the ability of a computer to learn a specific complex task from data or observations. CI methods can mimic human's way of reasoning to reasonable extent, using non exact and non-complete knowledge, to produce control actions in an adaptive way.

CI is based on fuzzy logic, case-based reasoning, neural networks, evolutionary computation, learning systems, probabilistic methods, nature-inspired systems, artificial immune systems, artificial neural networks and swarm intelligence. CI techniques facilitate intelligence in ever changing as well as composite environments through adoptive learning of mechanisms possessed by the system under study. For adoptive learning of the mechanism, we often use Artificial Intelligence (AI) paradigms that demonstrate an ability to gain insight or adapts to new situations through discovery, abstraction, association and generalizations. These techniques have been successfully applied to solve real-world problems individually. But the present trend is to develop hybrid CI paradigms, since no one paradigm can be used in all situations.

Sustainability is an ability to produce such a large quantity of energy which is enough to support biological and natural systems on earth. In the context of Computational Intelligence (CI), it is the computational power of computers to process complex data using sophisticated mathematical models, analytical techniques and fuzzy inferences. In agriculture, it attempts to optimize economic, environment and social resources to boost ability to produce enough food for human and animal consumption. Use of sustainable computing in agriculture can aid towards this endeavor using mathematical models and computer technology, focusing action taken and decision making for better economic gains viz-a-viz environmental protection.

4.1 Case Based Reasoning

Case-based reasoning is a four step approach to problem solving that draws attention to the role of prior experience during future problem solving. In other words, new problems are solved by reusing of prior proven intelligence and if necessary adapting the solutions to similar problems that were solved in the past [22]. This technique is a relatively newcomer to CI, which arose out of research into cognitive science, most conspicuously that of Schank [23–25]. Its basis was stimulated by a desire to understand how people remember information and are in turn reminded of information. Subsequently, it was recognized that people commonly solve problems by remembering how they solved similar problems in the past [26]. Conceptually CBR is usually represented by CBR-cycle as shown in Fig. 1 given by Aamodt and Plaza [27].

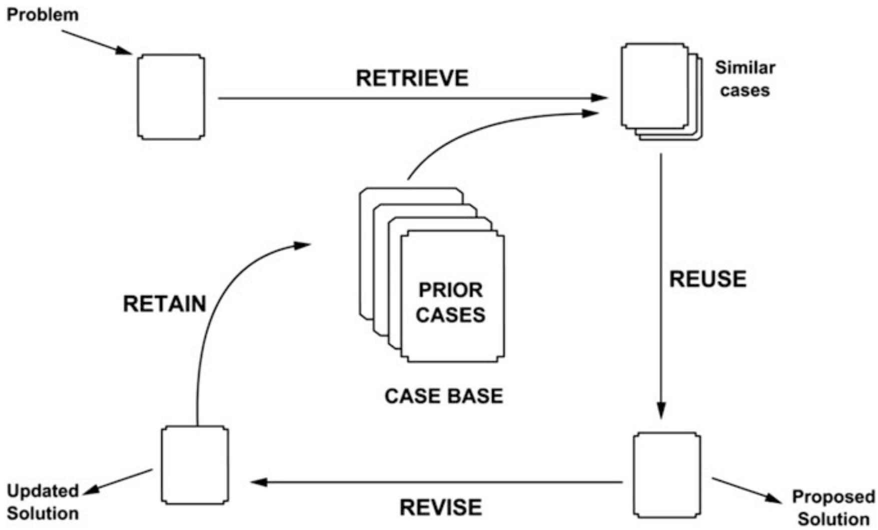

Fig. 1 The CBR cycle

This cycle comprises four activities popularly known as the 4RE's:

Retrieve similar cases to the problem description. This retrieve phase regains relevant cases form memory pertinent to the given problem. A case consists of a problem, its solution, and procedure about how the solution was derived. For example, IPM for apple fruit; here a farmer can recall most relevant experience using which he successfully controlled pathogens, together with the procedure he followed with justifications for decisions made along the way, constitutes IPM retrieved case.

Reuse a solution suggested by a similar case. Reuse phase maps the solution from the previous case. To the IPM problem, which may involve adapting the solution as needed to fit the new situation.

Revise that solution to better fit the new problem. After mapping the previous solution to the target situation, the revise stage tests the new solution, here in the context of IPM problem in hand. It may revise the procedure as per the current situation. In the perspective of IPM for apple, suppose there is a retained case for the control of sooty blotch with the recommendation, "Application of Mencozeb 75WP (75 g) per 100 L of water". The recommendation will be retrieved from the memory along with weather forecast, which suggests likely rainfall in next 24 h. Therefore, the case will be revised with the addition of "Spray with stickers or spray day after tomorrow".

Retain the new solution once it has been confirmed or validated. After successful adoption of the solution to the target problem, the resulting experience is stored in memory as a new case.

The guiding principle behind CBR is solving a problem explicitly through reusing a solution from a similar past problem. It retrieves cases from a case-library based on the principle of similarity of cases in the library to the current problem description. Then it attempts to reuse the solution suggested by a retrieved case with or without any revision. Eventually CBR systems increase its knowledge by retaining new cases.

4.2 CBR Techniques

CBR can be implemented using Nearest neighbour technique, Induction technique, Fuzzy logic technique and Database technology [27].

Nearest neighbor. Nearest neighbour finds case to case similarity of the problem in the case-library and determine attribute for each case. Then the measure is multiplied by a weighting factor. A measure of the similarity of that case in the library to the target case is provided by calculating sum of the similarity of all attributes. The process is represented by the Eq. (1).

$$Similarity(T, S) = \sum_{k=1}^{n} f(T_k, S_k) \times w_k \tag{1}$$

where T is the target case; S the source case; k the number of attributes in each case; f a similarity function for attribute k in cases T and S; and w the importance weighting of attribute k.

Similarities are usually normalized to fall within a range of 0–1 (where 0 is totally dissimilar and 1 is an exact match). The normalization can also be indicated as a percentage, where 0% would mean dissimilar and 100% an exact match. The use of nearest neighbour technique is well illustrated by the Wayland system [28].

Induction. Inductive retrieval algorithm is a technique that determines which features do the best job in discriminating cases and generates a decision tree type structure to organize the cases in memory [29]. This approach is very useful when a single case feature is required as a solution, and when that case feature is dependent upon others.

These techniques are commonly used in CBR. Induction algorithms, such as ID3 generates decision trees from case histories. All induction algorithms identify patterns amongst cases and partition the cases into clusters. Each cluster contains cases that are similar with the case in hand. Definition of target case is required in induction. Induction algorithms are importantly being used as classifiers to cluster similar cases together, wherein it is assumed that cases with similar problem descriptions will have similar solutions.

Fuzzy logic. Fuzzy logic is a way of formalizing the symbolic processing of fuzzy linguistic terms, such as excellent, good, fair and poor, which are associated with differences in an attribute describing a feature [22]. In fuzzy logic, number of linguistic terms is not restricted. Fuzzy logic intrinsically represents notions of similarity, since the linguistic values 'good' and 'excellent' are closer to each other than 'poor'. In order to find a solution to a problem, fuzzy preference function based on CBR can be used to calculate the similarity of a single attribute of a case with the corresponding attribute of the target.

Database approach. At its simplest form, CBR could be implemented using database technology. Databases are efficient means of storing and retrieving large volumes of data. If problem descriptions could make well-formed queries it would be straight forward to retrieve cases with matching descriptions. A problem along with using database technology for CBR is that retrieval of database using exact matches to the queries.

This is commonly augmented by using Wildcards, such as "WESTp" matching on "WESTMINSTER" and "WESTON" or by specifying ranges such as " , 1965". The use of Wildcards, Boolean terms and other operators within queries may make a query more general, and thus more likely to retrieve a suitable case, but it is not a measure of similarity. However, by augmenting a database with explicit knowledge of the relationship between concepts in a problem domain, it is possible to use SQL queries and measure similarity [27].

Hybrid approach. Hybrid approach uses more than one technique as described above to solve diverse problems. Similarly, the earlier studies [30–32] have addressed the hybrid fuzzy approaches for intelligent decision making process.

5 Towards Computational Intelligent DSS for IPM

Application of CBR to IPM is quite relevant considering different representation cases, requirement of past experience and wide range of possible responses. This section presents an intelligent computational solution based on the principles of CBR methodology using database approach which will be developed and implemented on World Wide Web. CBR has been selected due to its ability to consider past experience, provides representative cases which are similar to current problems, and provides solutions which take into consideration a range of possible responses.

An intelligent component to support decision-making is able to integrate existing phonological data related to pests and current weather conditions to support pest population predictions at economic and injury threshold levels. Beyond economic threshold level appropriate action as per the package of practices issued by the competent authorities shall be performed automatically by the system. As IPM requires past experience, efforts have been made where the system can learn from new situations and contributing to timely delivering interventions that benefit intended growers.

5.1 Computational Intelligence Techniques Used

In this research, induction technique and database approach are used together by extracting their relative potentials to address IPM of apple. The approach is used keeping in view unstructured nature of the knowledge base of IPM. Partitioning feature of induction technique and matching capability of database approach has been combined to get a CBR algorithm best suited for pest management problem. This study develops IPM intelligent agent comprising of two modules where the main interface is as shown in Fig. 2.

First module addresses the periodicity of different sprays as per the phonological stages of apple tree keeping in view current weather conditions. For which a similar case like the one in hand is retrieved from the database using MYSQL's data manipulation command *Select*. The case is then partitioning into clusters using *wildcards*.

Firstly, using *select* most appropriate or similar case is identified from the multi-lingual knowledge base. Due to bi-lingual and unstructured data, wildcards are used to partition the data into desirable segments so that the recommendations will be organized into a most interpretive manner. The algorithm used for this purpose is given hereunder:

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Retrieve description from knowledge-base where case = present phonological stage;
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Fig. 2 Main interface of intelligent agent for apple IPM

Partition *description* using *wildcard* (^) based on languages to get *Partition [0]* and *Partition [1]*;

Based on language option **Partition** *Partition [0]* using *wildcard (1)* to get *Recommendations* and *Warnings* in the said language;

Partition *Recommendations* to get *segmented* options of *Spray*;

And **Partition** *Warnings* to get *segmented* options of *Warning*;

Reuse *Recommendations*;

Reuse *Warnings*;

Revise *description* with the present and future predicted weather conditions;

Retain *description* for future use;

Second module performs symptom based disease diagnosis, wherein based on one or more symptoms, similar case is retrieved from the multi-lingual knowledge base using *Select* command of MYSQL's data manipulation. For multiple symptoms, the revision is done and the same is retained for future use. Here, new symptoms if any are added to the image database.

The case is portioned in the form of disease introduction, life cycle and control measures based on the language option selected by the user. The CBR algorithm used for this purpose is as under:

Retrieve *description* from knowledge-base where *case* is similar to symptom(s);

Partition *description* using *wildcard* (^) based on languages to get *Partition [0]* and *Partition [1]*;

Based on language option **Partition** *Partition [0]* using *Wildcard (1)* to get *introduction, life cycle and control measures* in the said language;

Reuse *descriptions;*

Revise *control measures* with the present and future predicted weather conditions;

Retain *description* for future use;

5.2 Description of the Intelligent IPM DSS

The overall working of the system is divided into two modules viz., Spray schedule and Disease diagnosis.

Spray schedule module. This module gives recommendations for chemical sprays based on the phonological stage of apple tree and weather condition. Fourteen phonological stages of apple fruit development such as Dormant, Silver

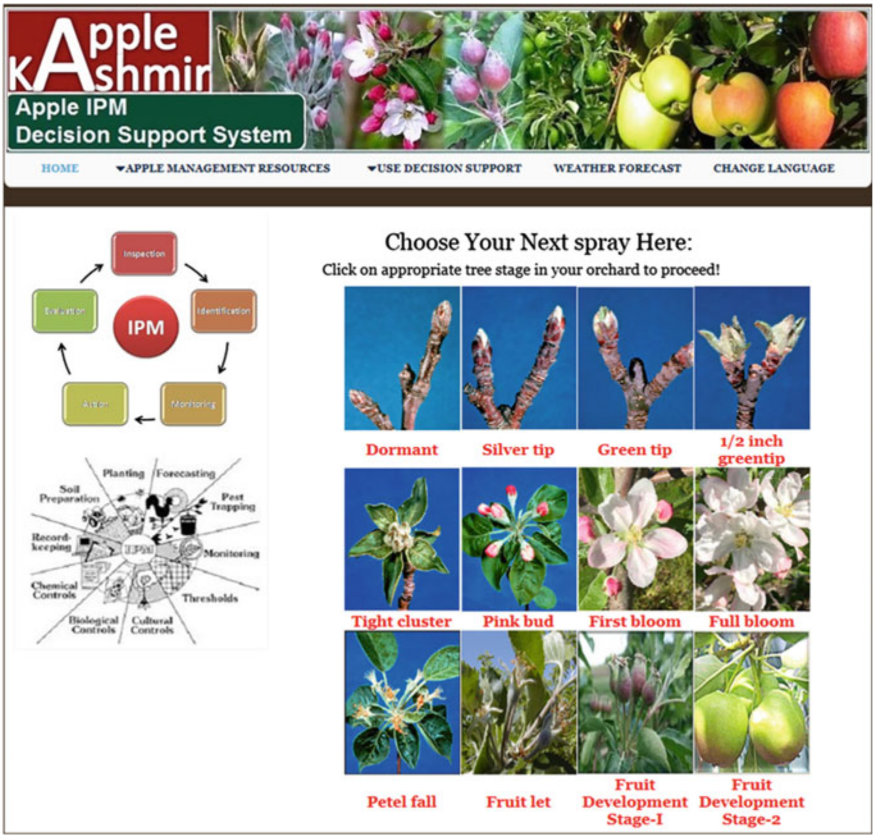

Fig. 3 Phenology based spray schedule

tip, Green tip, Half inch green tip, Tight cluster, Pink bud, First bloom, Full bloom, Petal fall, Fruit let and four stages of actual fruit development. This spray schedule interface is as shown is Fig. 3.

While user clicks on the appropriate stage, the system applies the algorithm stated already to get the next spray to be used in the orchard. For illustration, assuming that the user chooses Petal fall stage, the system generates spray recommendations for that stage with the warnings as shown in Fig. 4. Here stages are assumed having different cases. Users can reuse information unless the knowledge base will be modified and retained with the findings of new research.

Disease diagnosis module. This module helps to diagnose diseases pertaining to apple pests and diseases based on symptoms, which have been incorporated in the form of pictures categorized under different parts of the tree. Here user first selects the part in which disease has been noticed to emerge using the interface shown in Fig. 5. This has done to minimize the search space to improve response time. Then disease symptoms pertaining to that part are displayed, wherein user can select one

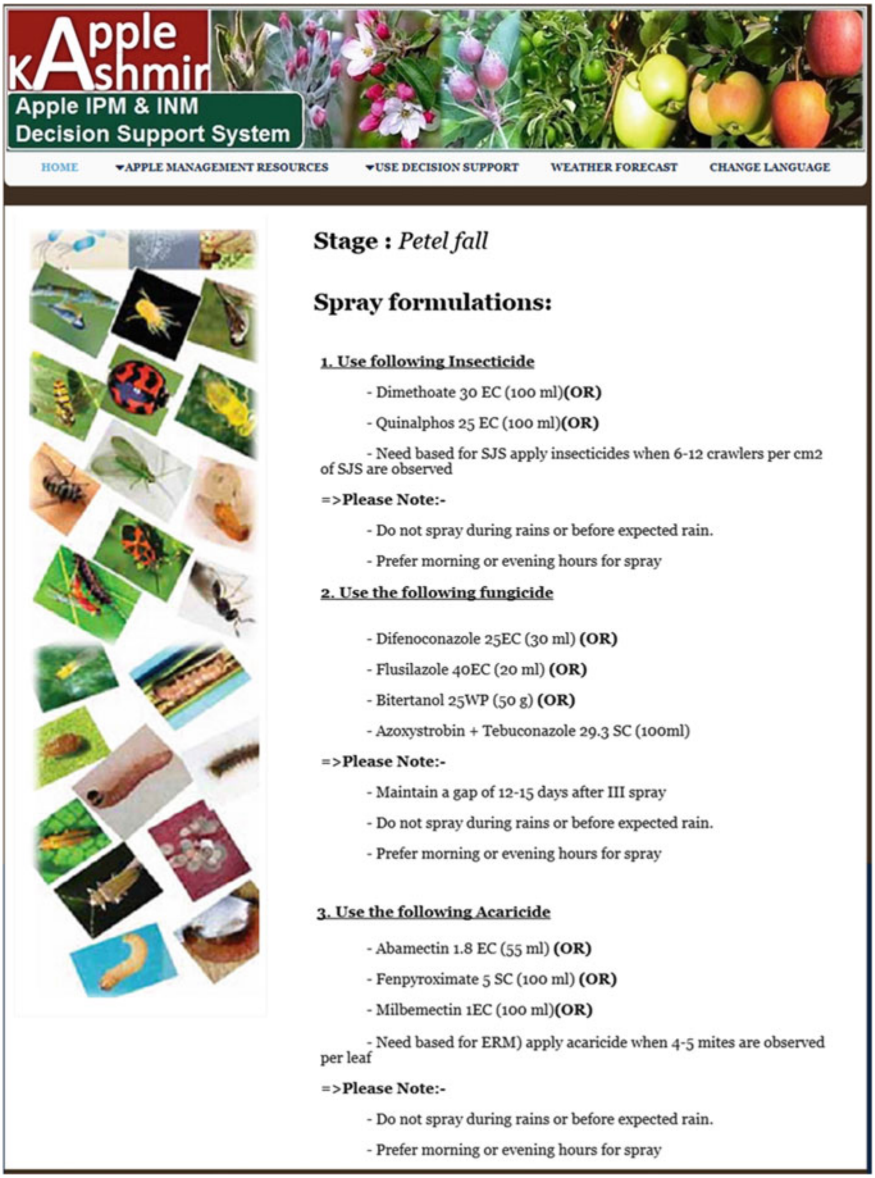

Fig. 4 Recommendations for petal fall stage

or many symptoms based on their observations in the field. The system retrieves similar case from the knowledge base, based on the algorithm given already. The retrieved information can be reused based on the symptoms. Knowledge base can be modified by the domain expert whenever new recommendations for a particular

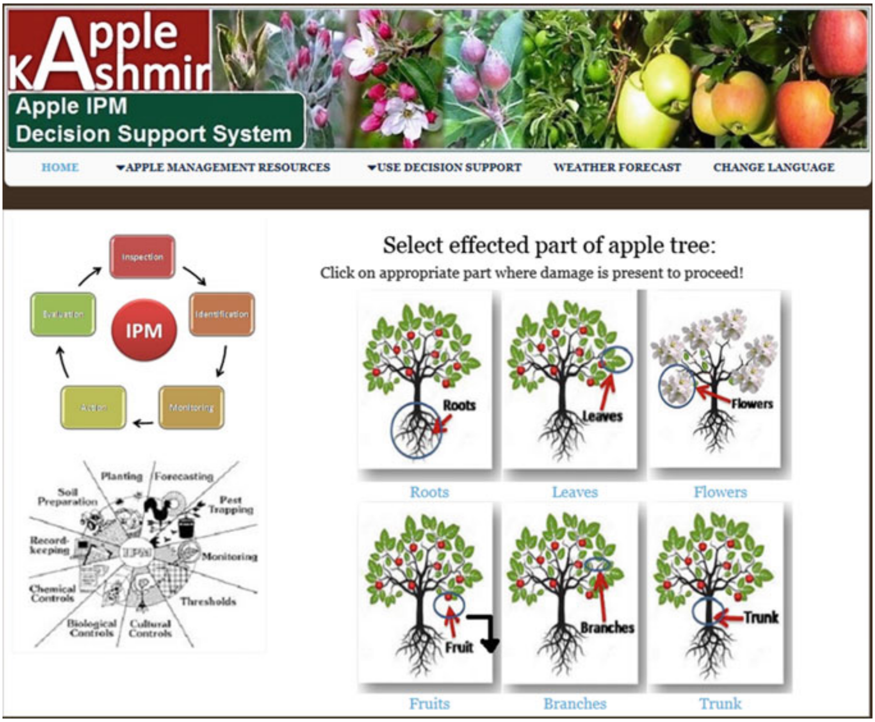

Fig. 5 User Interface for symptom based disease diagnosis

disease emerge. Finally the case is retained in the knowledge base for future use. For illustration, assuming user notices some symptoms on the fruits and chooses fruit part as diseased part using the interface shown in Fig. 5. Then the system generates suitable case for that part in the form of indexed pictures indicating symptoms as shown in Fig. 6. Here let's assume that the user choose picture indexed by number thirteen (13) as the symptom, then the system retrieves case with similar case description and generates recommendations automatically keeping in view present phonological stage with the warnings if any. Users can reuse this information unless the knowledge base will be modified and retained with the findings of new research. Assuming that the present phonological stage is peanut stage, the recommendations generated by the system is shown in the Fig. 7.

6 Results and Discussion

Design, development and evaluation of agricultural DSSs have widely been documented in literature [33–35]. However design and development of intelligent IPM DSS follows as related research [36–39], in which knowledge base design

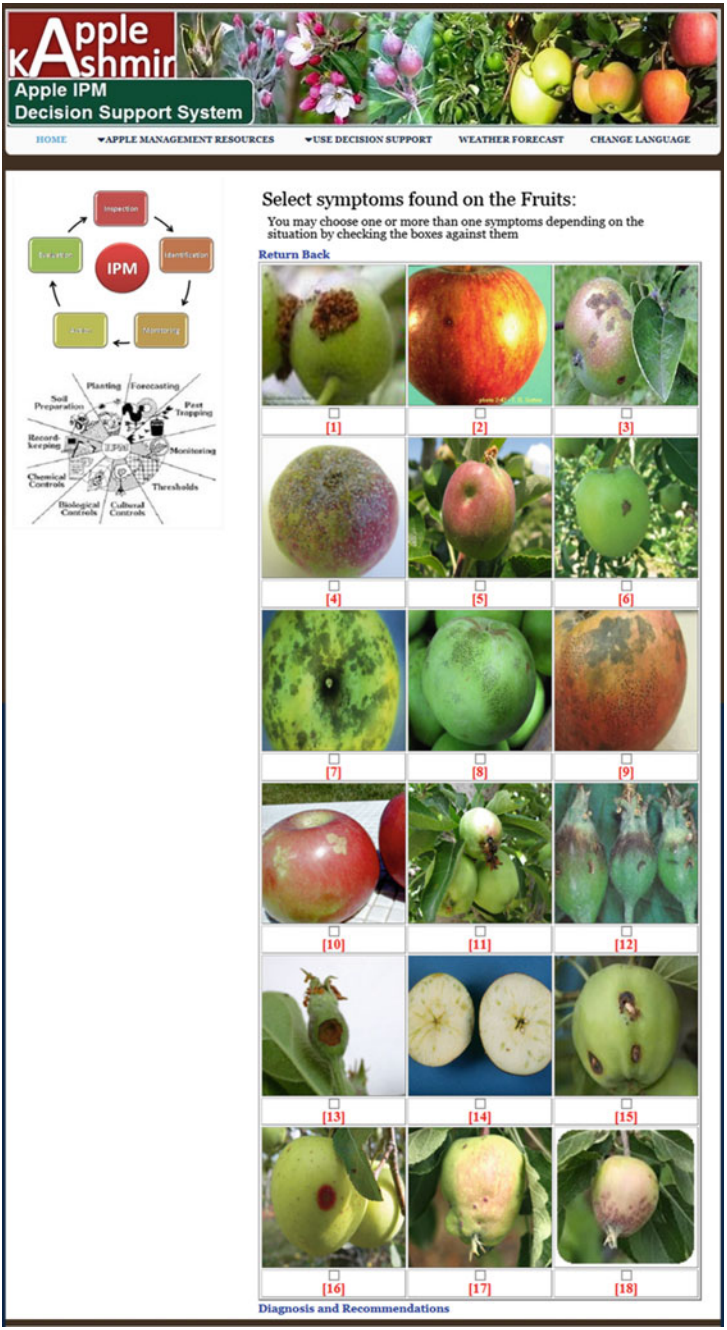

Fig. 6 Apple fruit disease symptoms

Fig. 7 Recommendations generated for fruit worm at peanut stage

comprises 15 pathogens already identified by the domain experts pertaining to apple prevalent in the temperate regions of India (Table 1). Technically, for better uptake of any agricultural DSS, it is delivered on the web; provides an easy and complete user-friendly interface; enables continuous and flexible access; automate and integrate data from multiple sources; helps in decision-making and not attempts to replace decision-maker; use validated models and involve all stakeholders [35]. Therefore, client-server web-architecture with hypertext manipulation language and the hypertext preprocessor PHP as front end and MySQL as backend were used so that the system exhibits continuous and flexible build–in dynamic query access; automate and integrate weather data from multiple nearby sources and can be accessed by all regional apple fruit growers. Besides, easy interface with pictorial inputs were designed for the end users. Every effort was made to use validated models and involve all stakeholders in the development process.

For usefulness and adoption, outcome is very important aspect of any DSS [39]. Research studies also envisage that users should be satisfied with the outcome of DSS [40]. In order to study the outcome of DSS with respect to sampling

Table 1 Details of pathogens modeled in the system

Common name	Scientific name
San Jose scale	*Quadraspidiotus perniciosus*
Woolly apple aphid	*Eriosoma lanigerum*
European red mite	*Panonychus ulmi*
Codling moth	*Cydiapomonella*
Powdery Mildew	*Podosphaerea leucotricha*
Root rot	*Dematophora necatrix*
Cankers	*Botryosphaeria spp.*
Apple Mosaic	*Apple Mosaic Virus*
Leaf and fruit spot	*Entomosporium maculatum*
Marssonina blotch	*Marssonina coronaria*
Sooty blotch	*Gloeodes pomigena*
Fly speck	*Schizothyrium pomi*
Apple Scab	*Venturia inaequalis*
Alternaria leaf blotch	*Alternaria mali*
Collar rot	*Phytophthora cactorum*

procedure, 383 trial cases involving domain experts comprising of Entomologists and Plant were conducted. The maximum scores that an evaluator could obtain was 100% (If all decisions made by the systems satisfies him/her) and the minimum score that a respondent could obtain depending upon number of satisfied decisions minus number of un-satisfied decisions. The summary of trial cases and accuracy of the decisions are indicated in the Table 2.

The trial cases conducted for judging efficiency of the system were of two types of decisions supported by the system viz., spray recommendations and disease diagnosis. For spray related decisions, 10 trail-cases were evaluated by all experts. The ten trial cases were different identified phonological stages for which sprays and their compositions were recommended. Concept of retrieve, reuse, revise and retain was demonstrated so that processed information can be retrieved and reused until it is applicable. Once new findings in the form of sprays and their formulations are found, knowledge base could be revised and retained accordingly. For spray decision process, fruit development stages were divided into 12 phonological stages from dormancy to post harvest stages. These stages were: dormancy, silver tip, green tip, pink bud, peanut, fruit development stage-1, fruit development stage-2, fruit development stage-3 and fruit development stage-4. Under these categories different recommended sprays for pathogens were collected and their associated knowledge base was developed. The only input demanded by the system is selection of the stage. The system generates probable stage(s) which are subject to validated by the users. The results of the trial cases suggest that 100% accuracy was found in the recommendations made by the system pertaining to the 10 user cases defined by spray recommendations.

However, for evaluation of disease diagnosis module, varied number of trail cases was performed by the experts due to diverse expertise of the experts as well as

Table 2 Summary of trial cases and accuracy of the decisions made by the system

Experts	Spray recommendations (N = 100)				Disease diagnosis (N = 283)				Overall accuracy (in %)
	Use-case	No. of accurate decisions	No. of inaccurate decisions	Accuracy (in %)	Use-case	No. of accurate decisions	No. of inaccurate decisions	Accuracy (in %)	
E-1	10	10	–	100	26	24	2	92.31	96.16
E-2	10	10	–	100	32	26	6	81.25	90.63
E-3	10	10	–	100	35	34	1	97.14	98.57
E-4	10	10	–	100	29	28	1	96.55	98.28
E-5	10	10	–	100	41	38	3	92.68	96.34
E-6	10	10	–	100	22	22	0	100.00	100.00
E-7	10	10	–	100	17	15	2	88.24	94.12
E-8	10	10	–	100	38	35	3	92.11	96.06
E-9	10	10	–	100	25	20	5	80.00	90.00
E-10	10	10	–	100	18	16	2	88.89	94.45
Total	100	100	–	100	283	258	25	90.92	95.46

multitude of the diseases and pests together with diversified nature of symptoms for a disease and disorder found in the apple. The trial cases were performed based on the expertise and availability of time with the experts. For disease diagnosis process, apple disease, disorders and pathogens were divided into six categories based on the different parts of the trees. These categories were: root, stem, branches, leaves, flowers and fruits. Under these categories varied number of diseases, pests and disorders known to exist in the study area were identified and their associated knowledge base developed.

The knowledgebase comprised of introduction, symptoms, life cycle and remedial measures were implemented so that farmers as well as students can get benefitted. The results of the evaluations suggest that minimum 17 user cases were evaluated by the Expert ‘E-7’ and maximum user case of 41 were evaluated by the Expert ‘E-5’. Maximum accuracy (100%) was reported by Expert ‘E-6’ with 22 user cases. While as minimum accuracy of 80% was reported by the Expert ‘E-9’. Overall, for disease diagnosis, 283 user cases were performed in which 258 cases were found accurate and 25 decisions were found inaccurate. The overall accuracy was 95.46%. The nature of inaccuracy exhibited by the intelligent decision support system has been documented and it shall pave the way forward to improve the performance of the system.

7 Scope, Significance and Limitations of the Study

The computational algorithms applied in this research can be used for the development of computationally intelligent IPM for the other crops. In this study, the algorithm was used to provide optimum spray decisions, disease identification and treatment pertaining to the apple, which finds great significance in precision disease management research. However, only a limited number of pathogens have been modeled. Besides the algorithm presented hereby can work efficiently on a suitable database schema, wherein different wildcards will mean different things for the algorithm.

8 Conclusions

In this chapter, hybrid case based reasoning computational intelligence techniques have been presented for pest management in apple. The technique uses four stage process of case based reasoning methodology viz., retrieve, reuse, revise and retain. The retrieve process is implemented in association with the matching logic performed on the knowledge base. The knowledge is presented in suitable format for the end user who reuses the same until the same is revised by the domain experts to incorporate latest research findings. The retain process is incorporated by storing the knowledge in the knowledge base. For sustained development of apple production, computationally intelligent techniques based decision support system has a role to play, in order to handle knowledgeably the vague multifaceted nature of IPM. The proposed Intelligent IPM decision support agent reduces the complexity of decision making to workable dimensions.

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