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# A Review of Knowledge Engineering towards High-Level Agro Intelligent Blackboard System Modeling

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## ABSTRACT

A blackboard system is an artificial intelligence strategy based on the blackboard architecture, in which a shared knowledge base, or "blackboard," is revised iteratively by many specialized sources of knowledge starting with a problem statement and ending with a remedy. This research paper presents a review of knowledge engineering towards modeling high-level agro intelligent blackboard systems. The paper reviewed knowledge engineering and its role in building expert systems. It explored statistical methods of direct observation and interview method as the methodology to extract knowledge from Agricultural extension workers, farmers, and agrochemical dealers. The data extracted were used to transfer the knowledge gathered to model a blackboard system that will later form a basis for any researcher that comes across it to develop and implement a knowledge-based system that is both robust and integrated, serving as a system for fast and accurate information transmission or as a weed control advisor for farmers in the absence of an expert to provide such assistance.

Keywords: Knowledge Base, Expert, Knowledge Engineering, Extension Worker, Blackboard, Agriculture

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## 1. INTRODUCTION

Knowledge engineering used to be primarily focused on building and developing knowledge-based solutions, which placed the topic in, at best, a specialized area of worldwide research efforts. This has drastically changed: in the impending knowledge society, knowledge engineering is now a key technology.

Companies are realizing that knowledge is one of their most valuable assets and that it must be utilized and safeguarded in a volatile, international, and cutthroat business environment. Due to this circumstance, knowledge engineering methodologies are currently being used in knowledge management [19]. One of the many techniques of knowledge organizing and exploitation that have been developed is the Blackboard architecture. It uses many problem-solving agents and is a member of the class of distributed problem-solving architectures. This paper comprehensively reviews Knowledge Engineering toward modeling high-level Agro-Intelligent blackboard systems. The architecture for creating systems for addressing problems is discussed using a blackboard system. Several autonomous processes, including expert systems, databases, or other knowledge sources in the application domain, communicate through a central global database known as the blackboard [8]. The problem-solving process is effectively coordinated by building up partial solutions on the blackboard. A blackboard system's characteristics include concurrent, incremental, and adaptive operation [8].

## 2. REVIEW OF KNOWLEDGE ENGINEERING AND RELATED RESEARCH WORK ON EXPERT SYSTEMS IN AGRICULTURE

There are various research works on Knowledge-Based Expert Systems. This section reviews various related research works on Knowledge-Based Systems toward building an integrated knowledge-based expert system called the blackboard system.

### 2.1 Review of Expert System in Agriculture

Numerous areas of science and business have successfully developed and used expert systems. Additionally, it can be used in agricultural operations to help farmers choose the best crops for their farmland. In the areas of crop management, farm evaluation, irrigation scheduling, fertilization regimens, disorder diagnosis, disorder treatment, etc., numerous expert systems have worked remarkably effectively and efficiently. This research study reviews applications of an expert system for diagnosing crop diseases from various studies conducted across the world in this section to evaluate how farmers use the system and the benefits they receive. This is necessary to examine the levels and volumes of research work in the past to direct towards achieving the aim and objectives of this paper in designing a model for integrated Expert Systems called blackboard systems for general farming information that may be needed by farmers on a timely basis. [6] designed a diagnostic expert system solution for diagnosing crop diseases and pests that has the potential to give farmers expert guidance. In the agricultural industry, the creation of knowledgeable systems for dealing with crop diseases and pests was emphasized, in addition to their being generally advantageous for the growth of research endeavour.

The study detailed the information learned from the recommended framework, which might aid researchers in highlighting problems in the agriculture domain and the tendencies of approaches that could be used. This study also provided some ideas that can be extremely helpful in future studies for the creation of an agriculture-related expert system. In order to manage rice and wheat, [5] has developed a framework for an expert system based on architectural rules. This method aims to detect insect-related symptons in wheat and rice plants. This intelligent system offers a user-friendly dashboard to assess user responses to questions regarding certain illness symptoms. It predicts the disease condition based on signs and user interactions.

Additionally, it presents a brand-new approach to knowledge representation in ES for the agriculture sector. [13], [10], and [12] have examined the numerous expert systems in use across the globe in agriculture. The authors emphasized that expert systems are more beneficial than conventional methods. Using an agricultural expert system boosts crop production. The farmers may simply use the expert systems to obtain professional recommendations from the system since they interact with the farmers' regional language. The Meghalayan paddy crop expert method has improved agricultural productivity and brought about enlightenment. With the help of this expert system, farmers may quickly learn about diseases, saving them time and reducing production losses. The English language is used to construct a lot of expert systems. Creating an expert system in the local tongue will raise their usefulness and help them get in-depth knowledge to boost production, overcoming the restrictions posed by the language barrier.

The web-based expert system will give farmers access to online expert assistance and could be accessible by anyone, anywhere. The authors have developed an effective and efficient expert system. [9] has applied the expert system for mango deformities disease management with success. The technique aids in measuring the prevalence of mango deformity conditions and selecting the best treatment plans. For the transmission of technological and scientific information in agriculture, This expert system benefits from the creation and design of a similar one. Increased production will also make it easier for agricultural expert systems to function. [18] proposed an expert system for ragi, a type of finger millets grown in Karnataka, which is the state's principal or essential food crop.

This essay emphasizes the agriculture industry's remedial measures and disease control measures. It was claimed that the first step in managing diseases is to identify those that cause crop disruption and a decrease in the product line. Calculated losses are applied along with the practical application of appropriate chemicals to eradicate the illness and increase crop yields. The adoption of Integrated Disease Management (IDM) helps to boost earnings and decrease liabilities. Productivity can be increased by combining multiple modules, such as soil, fertilizer, and integrated pest management. The expert system acquires new knowledge by gathering data on numerous disease-related attacks that took place on crops.

### 2.2 An overview of the knowledge engineering modeling process

Recently, there has been a lot of consensus that developing a Knowledge-Based System (KBS) may be viewed as a modeling endeavour. The creation of a computer model that can handle problems like a specialist might be considered as a similar process to constructing a knowledge-based system. Instead of just creating a cognitively acceptable model or broadly imitating the cognitive processes of an expert, it is required to construct a model that offers equivalent outcomes in problem-solving for difficulties in the area of focus. Although the expert may share part of his or her expertise out loud, a significant chunk will be kept secret in the expert's subconscious. Since it is not instantly accessible, this knowledge must be gathered and structured during the knowledge acquisition process. As a result, this process of knowledge acquisition is now seen as a process of developing models rather than a process of transferring knowledge into a suitable computer form. [1][3], [7].

### 2.3 Modeling Frameworks

Three modeling frameworks that handle distinct facets of model-based KE techniques are described in this section: CommonKADS [15] has outlined the structure of the Expertise Model; MIKE [1] stresses a written and operational definition of the Expertise Model as the result of the knowledge acquisition phase; and PROTÉGÉ-II [4] makes use of ontologies. The existence of additional methods that are well recognized within the KE community, such as VITAL [17], Comment [16], and EXPECT [20], should be obvious. A consideration of each of these strategies, though, is outside the purview of this work.

#### 2.3.1 The CommonKADS Approach

KADS [15] and its subsequent development into CommonKADS [15] are well-known knowledge engineering methodologies. The creation of a collection of models, each of which depicts a different feature of the KBS to be built as well as its environment, is a fundamental aspect of KADS. Different Organization Models, Task Models, Agent Models, Communication Models, Expertise Models, and Design Models are identified by CommonKADS. While the previous four models attempt to replicate the organizational context in which the KBS will work and the activities that are carried out in the organization, the expertise and design model describes (non-)functional aspects of the KBS that is currently under construction.

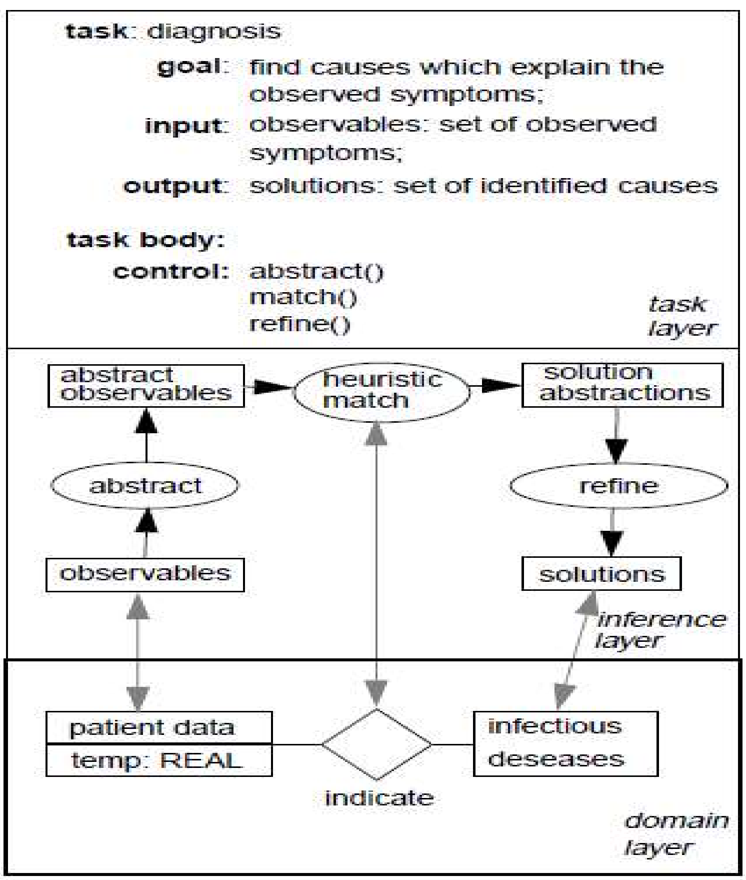


Figure 1: A Medical Diagnostic Expert Model (Simplified CML notation) [19]

### 2.3.2 The MIKE Method

An approach for developing KBSs that covers each stage, from initial extraction through specification to creation and implementation is provided by the Model-based and Incremental Knowledge Engineering (MIKE methodology [1,2]. Prototyping, formal and informal specification techniques, and engineering frameworks are suggested by MIKE. The inclusion of prototypes and support for a progressive and flexible system development strategy serve as the key differentiators between CommonKADS and MIKE. MIKE, which uses the Expertise Model of CommonKADS as its general model pattern, enables a seamless transition from a semiformal representation (Structure Model) to a formal representation (Design Model). The several representation layers of the Expertise Model must seamlessly transit amongst one another in order to support gradual and reversible system evolution in practice.

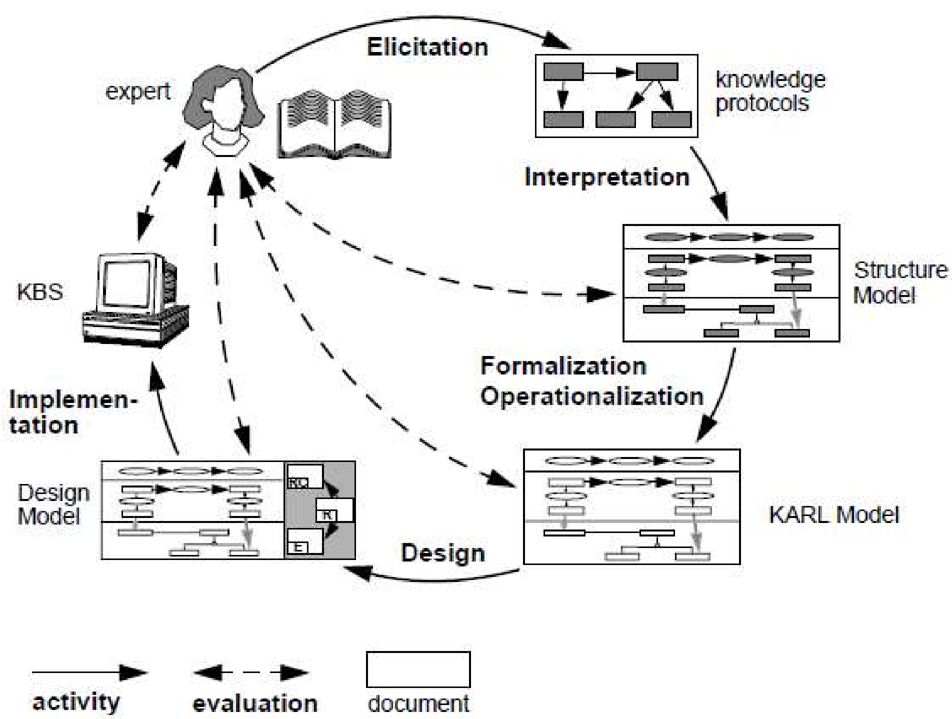


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Figure 2: The steps and documentation involved in creating MIKE [19]

### 2. 3.3 The PROTÉGÉ-II Methodology

The PROTÉGÉ-II approach [4,11], aims to encourage the creation of KBSs by reusing PSMs and ontologies. Furthermore, PROTÉGÉ-II emphasizes the development of knowledge-acquisition strategies that are specifically adapted to ontologies [6].

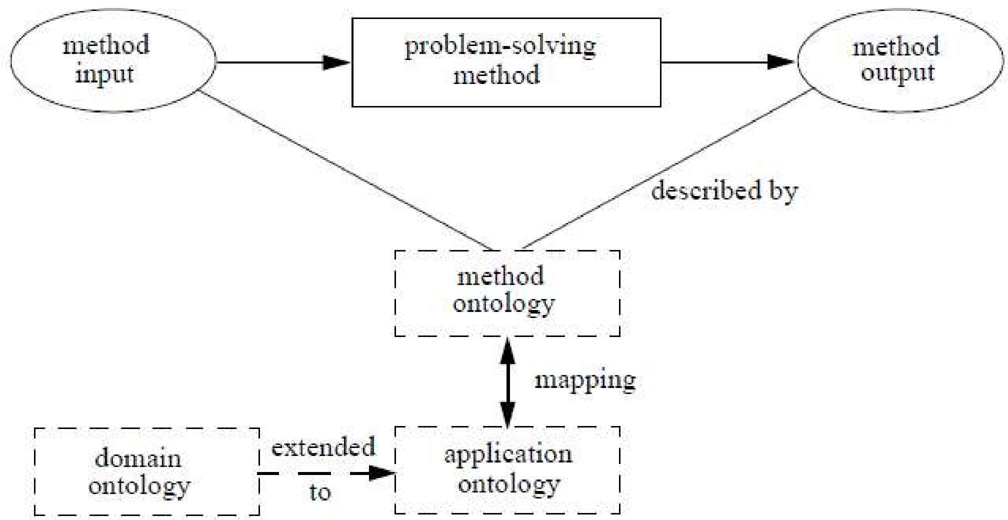


Figure 3: Ontologies in PROTÉGÉ-II [19]

## 3. KNOWLEDGE REPRESENTATION TOWARDS MODELLING HIGH-LEVEL AGRO INTELLIGENT BLACKBOARD SYSTEM

Knowledge Engineering involves a knowledge Engineer going to Expert(s) to extract and acquire knowledge in a domain area. Knowledge Engineer is the one who builds KBS or Expert System and May not necessarily know the chosen domain area. This section presents knowledge engineering towards achieving an Agro intelligent blackboard model for timely useful information to farmers.

### 3.1 Knowledge Acquisition Methodology

This study implored the statistical questionnaire, direct observation, and interview methods as the methodology to acquire and extract knowledge from Agricultural extension workers, farmers, and agrochemical dealers. The data extracted were used to transfer the knowledge gathered to a model blackboard system that will later form a basis for any researcher that comes across it to create and execute an effective, integrated knowledge-based (blackboard) system.

### 3.2 Knowledge Representation

CLASSIFICATION OF WEED CONTROL HERBICIDES for Pre-Emergence, before the weed, emerged, and post-emergence, after the weed emerged.

Table 1: Classification of Weed Control Herbicides

| | SELECTIVE | | NON SELECTIVE | |
|---|---|---|---|---|
| | Selective based on different crops | | | |
| Generic Name | 2-4D | Nicosulfuron | Glyphosate | Paracot |
| Actions | - Only broad leave or Dicot weed would be affected. i.e maize, guinea corn, and wheat would not be affected<br>- All monocot weed would not be affected | It will not kill only Maize | They are very toxic and will kill any weed in contact | They are very toxic and will kill any weed in contact |

A. 2-4D

| S/N | CODE | PRODUCT NAME |
|---|---|---|
| 1 | SA1 | Amino force |
| 2 | SA2 | SUN-2-4D |
| 3 | SA3 | Amino corn |
| 4 | SA4 | Festamine |
| 5 | SA5 | Amino Spry |
| 6 | SA6 | June-2-4D |
| 7 | SA7 | Select |

B. Nicosulfuron

| S/N | CODE | PRODUCT NAME |
|---|---|---|
| 1 | SB1 | Guard force |
| 2 | SB2 | INSTA Kill |
| 3 | SB3 | Nico action |
| 4 | SB4 | Relifron |
| 5 | SB5 | Striker |
| 6 | SB6 | Nico Sping |

Selective for Legume Family (Beans, Soya Beans, etc.)
C. Legume

| S/N | CODE | PRODUCT NAME |
|---|---|---|
| 1 | SC1 | Legum force |
| 2 | SC2 | Potassium |

D. DIURUM FOR TUBEROUS CROPS (for early and pre-emergence in yam, cassava, sweet potato, and other tuberous crops)

| S/N | CODE | PRODUCT NAME |
|---|---|---|
| 1 | SD1 | ARROW |
| 2 | SD2 | Potasum |
| 3 | SD3 | Rooter |
| 4 | SD4 | Diu View |
| 5 | D5 | Diuron |

Table 2: Some Selected Herbicides

| GLYPHOSATE-CONTACT SYSTEMIC | | | | PARACOT- QUICK ACTION | | |
|---|---|---|---|---|---|---|
| S/N | CODE | Brand Name | | S/N | CODE | Brand Name |
| 1 | NA1 | Glymor | | 1 | NB1 | Weed Storm |
| 2 | NA2 | Force Up | | 2 | NB2 | Gramazone |
| 3 | NA3 | Glyphosate | | 3 | NB3 | Paraforce |
| 4 | NA4 | Sarosate | | 4 | NB4 | Paramash |
| 5 | NA5 | Glyphotex | | 5 | NB5 | Para-Plus |
| 6 | NA6 | Uproot | | 6 | NB6 | Express |
| 7 | NA7 | Knockdown | | 7 | NB7 | Weed Off |
| 8 | NA8 | Prosate | | 8 | NB8 | Weed Storm |
| 9 | NA9 | Wurawura | | 9 | NB9 | Weed Cush |
| 10 | NA10 | Touch Down | | 10 | NB10 | Slasher |

| GLYPHOSATE-CONTACT SYSTEMIC | | |
|---|---|---|
| S/N | CODE | Brand Name |
| 11 | NA11 | Round Up |
| 12 | NA12 | Sunphosate |
| 13 | NA13 | Clear Weed |
| 14 | NA14 | Flyshate |
| 15 | NA15 | Dryshate |
| 16 | NA16 | Glyssshate |
| 17 | NA17 | Glymax |
| 18 | NA18 | Tackle |
| 19 | NA19 | Richclear |
| 20 | NA20 | Spashate |
| 21 | NA21 | Weed All |
| 22 | NA22 | Relysate |
| 23 | NA23 | Race Down |
| 24 | NA24 | Bush Clear |
| 25 | NA25 | Dell Sate |
| 26 | NA26 | Filtscosate |
| 27 | NA27 | Junephosate |
| 28 | NA28 | Relisate |
| 29 | NA29 | Springsate |

| GLYPHOSATE-CONTACT SYSTEMIC | | |
|---|---|---|
| S/N | CODE | Brand Name |
| 11 | NB11 | Parmor |
| 12 | NB12 | Sun Paraquat |
| 13 | NB13 | Dragon |
| 14 | NB14 | Royalquat |
| 15 | NB15 | Paraqem |
| 16 | NB16 | Weedless |
| 17 | NB17 | Para Seal |
| 18 | NB18 | Pentagon |
| 19 | NB19 | Paraq |
| 20 | NB20 | Dayone |
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### 3.3 Blackboard Model for Agro Intelligent System

1. Blackboard Architecture

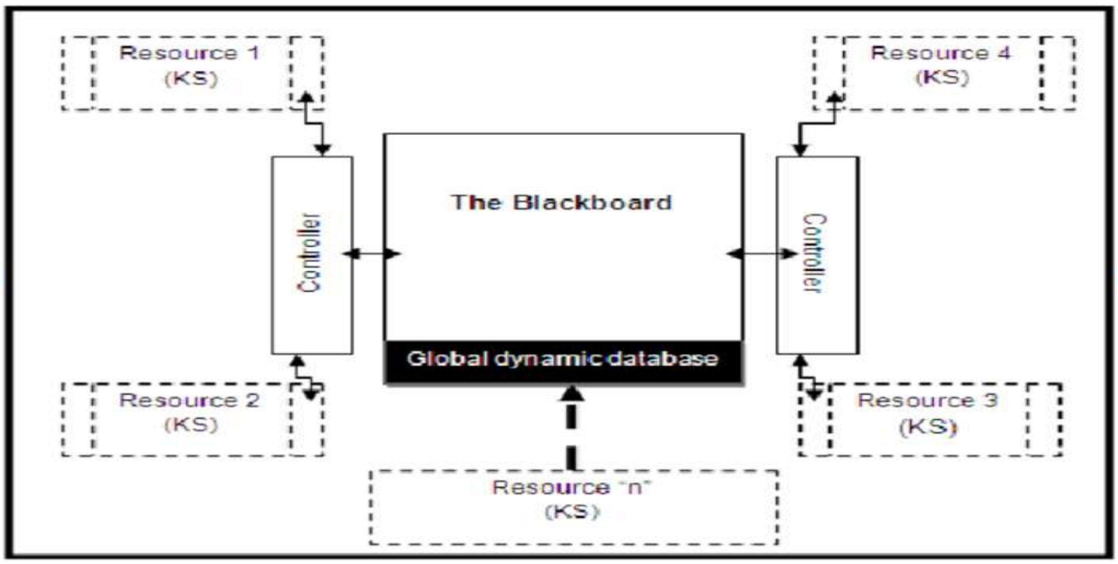



Figure: 4a Blackboard Architecture [14]

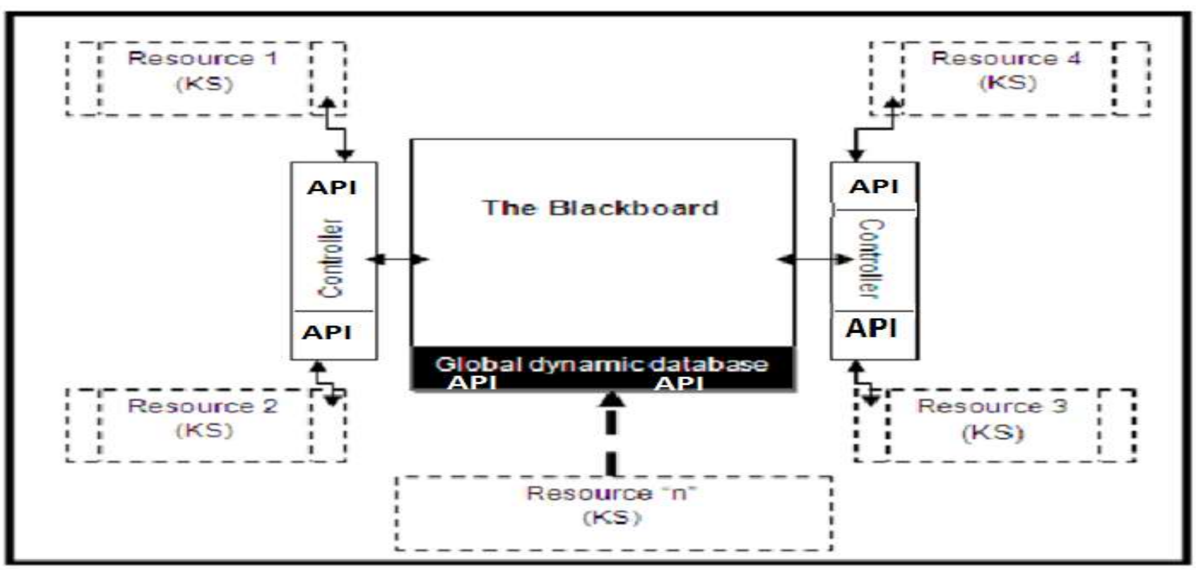
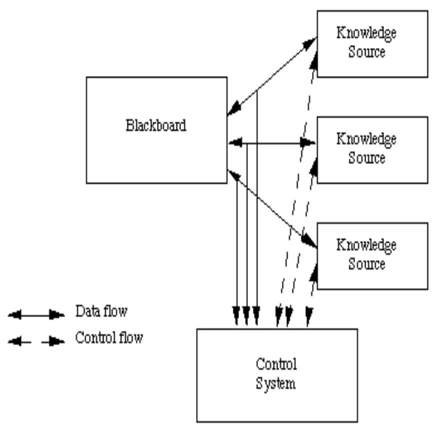



Figure: 4b: Enhanced Blackboard Architecture [14]

*2. Blackboard systems*

The figures below illustrated the basic idea of a blackboard system



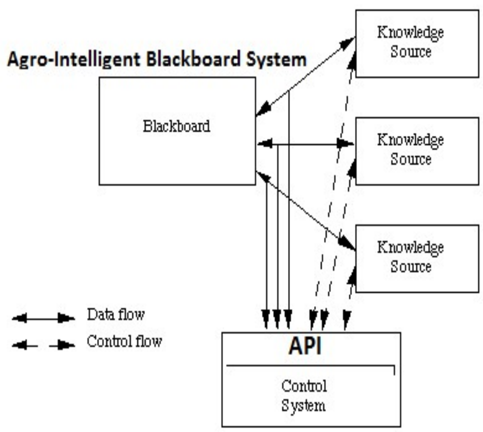




Figure: 5a Blackboard model [14]    Figure: 5b Blackboard (New model) [14]

The system is made up of knowledge sources, which are a collection of autonomous modules that store domain-specific information. It has a board, which is the common data structure used by knowledge sources to interact. It has a control mechanism that establishes the sequence in which knowledge sources will be applied to the entries on the blackboard.

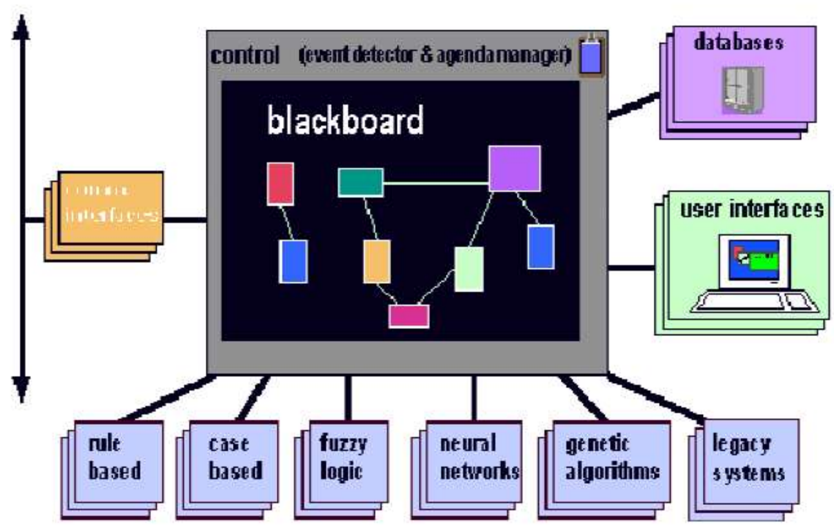



Figure 6: Different kinds of knowledge sources in the blackboard system [14]

## 4. CONCLUSIONS

This paper comprehensively reviewed Knowledge Engineering and the Knowledge-Based Expert system, it has also demonstrated Knowledge representation by carrying out a personal interview with an already prepared questionnaire with agricultural extension workers and agro chemicals dealers, the knowledge gathered on herbicides were represented in sections 3.2 and came up with enhanced blackboard system model.

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