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A MODEL FOR OVERCOMING DOMAIN KNOWLEDGE ACQUISITION AND VALIDATION CHALLENGES IN EXPERT SYSTEM DEVELOPMENT AND KNOWLEDGE ENGINEERING PRACTICE

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Abstract

Effectively managing domain knowledge acquisition challenges has been a major and persistent problem facing knowledge engineers while developing expert and knowledge based systems. Fear of losing job and becoming rendered irrelevant in their places of engagement demoralises domain knowledge experts and they are consequently unwilling to divulge important domain knowledge to Knowledge Engineers. Oftentimes, they are reluctant to cooperate when needed for the crucial product performance evaluation and validation too. Stiff resistance is sometimes encountered by knowledge engineers while in few notable cases, misleading, inaccurate or incomplete knowledge is deliberately released to stigmatise their product. These domain knowledge acquisition challenges had resulted in poor design and below-expectation performance products. This study proposed an improved Collaborative Consultative Knowledge Acquisition (CCoKA) model in Knowledge Engineering (KE) practice to address these challenges. By reviewing some of the leading existing KE product designs models, such as Rapid Application Development (RAD) model, Spiral model, and Common Knowledge Acquisition Documentation and Structuring (CommonKADS) model., this study identified the often overlooked root cause of the problem in many KE designs. CCoKA model fosters collaborative, reassuring and early engagement of domain knowledge experts in KE product development; in a way that specially dignifies domain experts and preserves their relevance. These will foster improved cooperation and support from the domain experts and consequently result in a much better Knowledge Engineering AI (Artificial Intelligence) product design and performance.

Key words: Knowledge Engineering, Domain Knowledge Experts, Knowledge Based Systems, Artificial Intelligence, CCoKA.

1.0 Introduction

Knowledge Based Systems (KBS) sometimes called Expert Systems (ES) and other related Artificial Intelligence products, are products of Knowledge Engineering (KE). They are applications that are specially designed and developed to simulate the wisdom, judgement and actions of a person or organisation possessing expertise in a particular field or set of fields with the use of Artificial Intelligence (Lutkevich, 2024). They often serve as substitute to human experts or in the least support the human expert in executing his professional tasks. These products have benefitted man in critical and life crucial specialist fields for decades. Such application areas include medical diagnosis and prognosis, automobile industry, security and safety systems, flight control and management, military expeditions, manned and unmanned space explorations and navigation, industrial control and monitoring systems, Internet search engines, social networks support systems, banking and agriculture advisory Decision Support Systems (DSS). These KE products are often employed to solve complex problems requiring human cognitive skills. They often help managers in crucial decision making in real time as they explore and analyse large amount of data to this end (Aswani, 2023). A knowledge engineer or group of collaborating knowledge engineers and domain experts are required to build such systems (Glyn, 2020).

As a subfield of Artificial Intelligence, (AI), Knowledge Engineering practice requires Knowledge Engineers to integrate domain specific knowledge into the computer systems for the purpose of solving problems complex enough to require the service of a human expert in that knowledge domain. Domain knowledge refers to that expertise in a professional that enables him to know what to do, why, when, where, and how to effectively manage a field-specific challenge. Such knowledge is an indispensably needed resource by. Knowledge Engineers who, as skilled computer professionals need to build advanced logic into computer systems such that these computer systems can simulate human in decision making activities and in carrying out roles requiring high-level cognitive skills. Knowledge engineer skillfully sources for the domain knowledge and incorporates same into the computer system via appropriate knowledge representation and coding scheme (Rudi, Benjamins & Dietel, 2017). Domain knowledge is a very crucial resource in robotics, machine learning, Artificial Intelligence (AI) and data science, and in training models to achieve good performance (geeksforgeeks.org, 2024).

Robotics, machine learning, data science, artificial intelligence, natural language processing and speech recognition fundamentally rely on knowledge engineering as their building block to develop real world applications and models (Farquhar, 2024). However, when knowledge engineers couldn’t secure the trust of domain knowledge experts, acquiring the domain knowledge needed to build these real life applications becomes unattainable, a cog in the wheel of progress.

Several approaches had been explored to achieve a breakthrough in this regard. The three approaches explored in literature are manual, automated and combined. Protocol analysis, grid analysis, structured interviewing, questionnaire administration and repertory grid analysis are examples of manual techniques used for eliciting domain knowledge from domain experts (Popovic, 2025). Consequently, some acquired domain knowledge had been cleaned, structured and stored in publicly accessible repositories like kaggle.com. As secondary data, such had been used by knowledge engineers in training and building real life AI models and applications like drones and other types of robots.

Above is however contingent on the cooperation, support and goodwill of knowledge domain experts. In cases where the domain experts are not willing to part with the crucial domain expert knowledge for whatever reasons, serious design and performance bottlenecks for knowledge engineers result.

Sometimes, in the advent of a local pandemic, civil unrest or any internally generated economic crisis, required knowledge for developing an effective real world solution in a timely fashion is better sourced as primary data from local domain knowledge experts, given the nature and peculiar locale of the problem instead of resorting to less relevant secondary data kept in a particular repository. However, when locally available knowledge domain experts fail to cooperate with the knowledge engineers, perhaps for fear of losing their relevance to technology, knowledge engineers might have no other choice but to use cloud sourced secondary data available in online depositories as substitutes. In many cases, such substitute data do not adequately meet the precise requisite needs of the knowledge engineer in respect of prevailing challenges.

Closely connected to this is the challenge of validating the quality and accuracy of the knowledge and data obtained in context of prevailing challenge and place, which cannot be perfectly achieved without the cooperation of the domain knowledge expert. All these had resulted in poorly designed products that perform below expectations. This in turn do result in preventable loss of resources and sometimes lives.

This further underscores the seriousness of domain knowledge acquisition challenges facing knowledge engineers in the course of developing direly needed artificial intelligence (AI) and machine learning solutions to real life problems. Finding a lasting solution to this problem is not only non-negotiable, it is also inevitable.

Shodhganga's (2018) shows the need for domain expert involvement during knowledge acquisition stage. However, over the years, literature shows that efforts had largely been concentrated on representing human (domain expert) knowledge with various techniques for the inference engine to be able to manipulate it in response to queries submitted via search features and search engines

2.0 Related Works

Durgaprasad (2021) listed and described semantic network, frames, rules, object-attribute-value triplet, logical representation and the hierarchical blackboard architectures (figure 3) as some of the knowledge representation approaches employed in knowledge based systems and expert systems development over the years.
Depending on the particular project at hand, the knowledge engineer could adopt manual knowledge acquisition approach, automated approach or combine the two approaches.

Wiliyanto, (2017) In a study conducted by Dian Atnantomi Wiliyanto to determine the effectiveness of web based expert system applications, he found expert systems effective in identifying and intervening to help children with special needs in inclusive schools. She recorded 52% result accuracy.

Adams, (2017) wrote also on Cogito as the generic name for various expert system software that come with built-in knowledge using a best of machine-learning and linguistic modeling approaches. Cogito products are of computational focused conceptual innovation. Use is made of semantic interpretation of language and programmatic logic. Subject matter expert knowledge is obtained through collaborative, manual and machine learning algorithms resulting in scalable multilingual application development support for multilingual development and extensive scalability. However, its operative machine learning and pattern recognition mechanism is strictly text based. Identification of graphical image data was not factored into its design.

Yusof (2018) proposed developing an expert system for agriculture using rule based and forward chaining inference engine in development of M-DCocoa in Malaysia. The program however does not factor the possibility of intruders hacking and corrupting the knowledge base of the system into design and thus preventing it from benefitting the rightful users as intended.

Santosa, Romla and Herawati, (2018) used Fuzzy Mamdani, to develop an expert system to detect and care for cataract eye disease based on the symptoms identified. From a sample of 50 cases, the software had 78% prediction accuracy compared with that of human experts.

Shodhganga (2018) compared several ES development models applicable in Agric and came up with a web based model (figure 2.5). He pointed out that ES is an expertise driven research area where researchers have many times used multi methodologies approach to develop ES. He added that Rule based system and KBS are the two methodologies often used for Agricultural ES. A flaw in the model however is the inability of the system to autonomously validate input and prevent data redundancy. The model also does not consider online knowledge acquisition and validation against security vulnerabilities such as when a non-domain expert poses as a domain expert. Thus, there is the need to develop a framework that autonomously verify and validate submitted piece of data or knowledge for validity and to avoid data redundancy.

2.1.1 Manual Techniques

Protocol Analysis, Card Sorting, Interviews, Observation, Repertory Grid Analysis, Surveys and Questionnaires are age-long manual techniques that have been used for knowledge elicitation in research, AI and in developing expert system. However, using these manual techniques requires the cooperation and support of respondents and custodians of knowledge being sought. Before the advent of modern automated AI tools, securing cooperation and support of such domain experts were much easier as long as data protection ethics are followed and guaranteed. However, the narrative is changing now that AI is effectively simulating and creating better and smarter replacements for these domain experts; resulting in fear of become irrelevant, obsolete unemployed and sidestepped grows.

2.1.2 Automated Techniques

Data Mining, Machine Learning, Natural language processing (NLP), and Automated Reasoning Systems are examples of automated techniques applied in knowledge acquisition for AI and expert system product development (Kerdprasop, & Kerdprasop, 2012;Vlaanderen, 1990). Tools making use of these techniques include AQUINAS, ASTEK, Auto-Intelligence, BLIP, and ETS among others.

Acquisition of STructured Expert Knowledge, ASTEK is an acquisition tool that offers to the knowledge domain expert and engineers, a clear intuitively designed form to fill as a way of eliciting needed domain knowledge from the expert. It then monitors the transfer of the same knowledge from the obtained external copy from the experts to an internal version. Easily, the inference engine can then support and correct the construction, rendering and manipulation of the internal version. ASTEK also offers knowledge management support activities such as incremental testing, revision and maintenance.

Auto-Intelligence is a knowledge acquisition tool designed for classification and diagnosis related problems. It operates by allowing the domain expert to select a problem category, define the characteristics of the problem selected and create corresponding examples. Based on these two inputs from the expert, Auto-Intelligence then builds a rule-based expert system.

Berlin learning by induction program, BLIP is capable of enabling the domain expert or the knowledge engineer to enter, inspect and manipulate obtained knowledge by using sorted logic and augmented higher order constructs.

Expertise Transfer System ETS, can effectively interview the domain expert, analyse the volunteered information and build corresponding knowledge base using production rules.

Features and functions of ETS were enhanced and advanced in another knowledge acquisition tool, AQUINAS. This tool is capable of building knowledge base based on knowledge obtained by decomposing problems, combining uncertain information, eliciting distinctions, testing knowledge and analysing deep and causal knowledge. It more importantly offers knowledge acquisition and maintenance guidance.

2.1.3 Combined / Other Related Techniques

Concept Sorting, Diagram Based Techniques, Literature Reviews, and Prototype Generation are some knowledge elicitation and acquisition techniques where researchers and knowledge engineers often combine manual and automated techniques. Their use is contingent on the cooperation of domain experts just the same.

All the three approaches: the manual, the automated and the combined approach have one gap in common. They are all based on the delicate presumption that the knowledge domain expert will undoubtedly cooperate with and support the process of knowledge acquisition initiated by the knowledge engineer. The automated machine learning dependent tools (ASTEK, BLIP, ETS, Auto-Intelligence, AQUINAS and many others) were designed and built to receive domain knowledge, from the expert, convert it from human to machine understandable form, structure same for ease of referencing, manipulation and presentation to users, without giving due considering to the possibility of the refusal of the domain knowledge expert to cooperate. Consequently, none of these systems is built with this possible challenge in mind.

2.14 Knowledge Acquisition System Architectures

As a distinct and prominent feature, the knowledge acquisition subsystem, the workspace, the application module and the knowledge refinement module were some significant components that had been added to the structure of expert system (Turban, Sharda and Delen, 2011). Atanasova and Krupka (2013) separated knowledge acquisition from ES shell and they reflected the presence of new elements such as interactive module, coordination module, rule editor and knowledge editor in design of modern ES (figure 1).

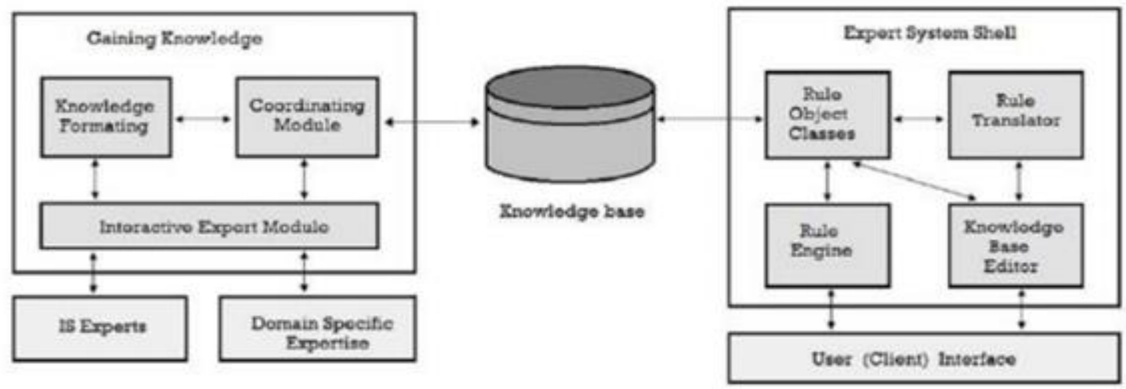

Figure 1: Modern Expert System Architecture. *Source*: (Atanasova & Krupka, 2013)

Nevertheless, this design however did not factor online autonomous knowledge acquisition, update and validation into their design model. It also left out referral features. Peter Lucas (2017) emphasized the need for modern ES to contain other components such as explanation facility and trace facility (Figure 2).

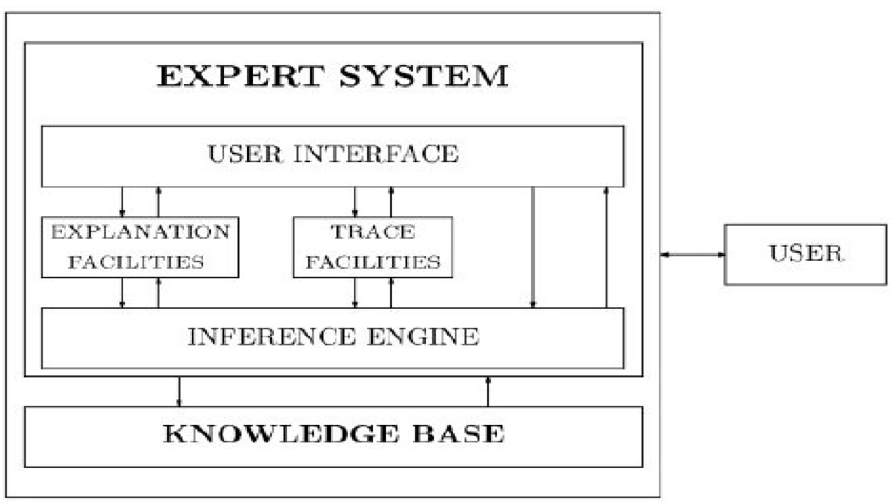

Figure 2: Global Expert System Architecture – (Source: Lucas, 2017)

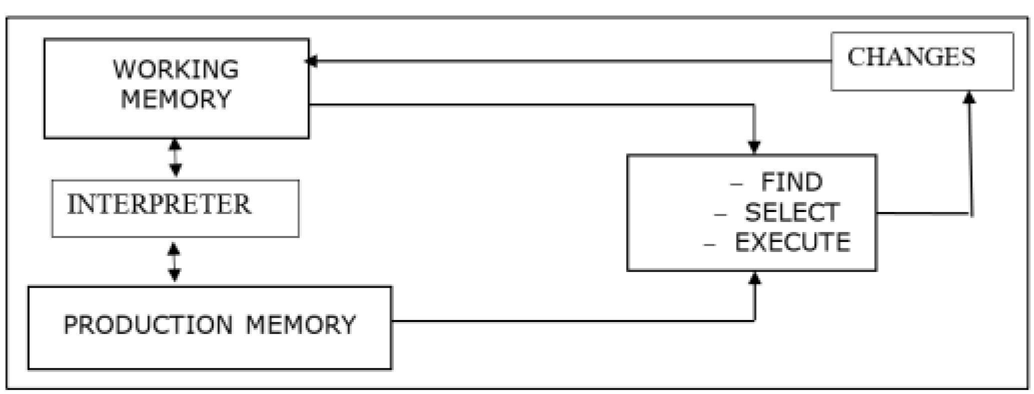

Figure 3: Blackboard Architecture (Durgaprasad et al, 2021)

In **Durgaprasad et al, (2021)** Blackboard Architecture attention is given to the trending shift in paradigm from rule-based to artificial intelligence based data driven approaches. Rule-based AI techniques achieve their inherent intelligence by applying rules to the input knowledge data while Data-based AI techniques obtain their intelligence from studying both the input and output data (referred to as training data) to resolve the rules of the problem (figure 3).

Vissers-Similon et al (2024) articulated and classified knowledge acquisition approaches employed in AI for knowledge and intelligence engineering systems according to emergence of this new trend (table 1).

Table 1: Classification of artificial intelligence techniques for intelligence and knowledge acquisition

S/No.	**CLASS**	**DESCRIPTION**
1	Agent based systems (ABS)	Reinforcement learning and swarm intelligence are both subcategories of agent-based systems (**ABS**), which consist of agents that have a certain rule-based autonomy and are often able to learn from training data.
2	Graph machine learning (**GML**)	a subfield of machine learning that works with graphs – mathematical data constructs that hold information about entities and the relationships between those entities.
3	Classic machine learning (**CML**)	techniques that use training data to learn in order to perform ‘classic’ tasks such as regression, classification and prediction, which includes neural networks, support vector machines and gradient boosting.
4	Generative machine learning (**GenML**)	techniques that learn from training data to create new data, such as generative adversarial networks or variational autoencoders.
5	Transformer models (**TM**)	Diffusion models and large language models are subcategories of Transformer models. They are extensively trained on large datasets and able to generate new data based on other kinds of data, for example generating images based on textual input.
6	Evolutionary computing (**EC**)	Genetic algorithms are a subcategory of evolutionary computing (**EC**), a field where algorithms are based on biological rules.
7	Expert systems (**ES**)	contain an embedded database of expert knowledge and are able to infer new knowledge by applying rules to the existing knowledge.

Apparently, literature had shown so far that attention had been concentrated more on perfecting representation and manipulation of already acquired knowledge than ascertaining successful acquisition of the knowledge in the first place.

Consequently, in order to address this challenge, this study proposed Collaborative Consultative Knowledge Acquisition (CCoKA) model as an improved knowledge acquisition framework in knowledge engineering. CoKA factors the interests, welfare (perhaps in form of royalties) and post product design and implementation relevance of the domain knowledge experts into design and development of the product through a friendly and interactive engagement. This definitely allays domain knowledge expert’s fear of becoming irrelevant, sidetracked, unemployed and replaced by AI / expert systems. By extension, it thus addresses the knowledge acquisition challenges causing design and performance bottlenecks apparent in KE in general. It also fixes or eliminates reluctance of domain experts to be involved in product performance validation and update challenges since the cooperation of relevant domain knowledge experts would have been secured.

3.0 Methodology

Integrated literature review adopted for this study clearly revealed that overcoming this isolated but often overlooked knowledge acquisition challenge in knowledge engineering requires making adjustment to architectural design of knowledge engineering systems (Expert Systems inclusive.) to embrace and include domain expert friendly collaborative consultative sub-stage as shown in figure 4. At this stage, the knowledge engineer approaches the domain knowledge expert to convince and assure him of continuous relevance as he solicits his cooperation and support. To achieve this, the knowledge engineer might enlist the help of skilled orator as his research assistant. Sound and ethical agreement on compensation and remunerations perhaps in the form of royalty payments may be necessary to assuage the fears of the domain knowledge expert and facilitate their cooperation and support. Figures 1-3 above show some of the hitherto used architectural designs for KE products development as opposed to the proposed architecture Collaborative Consultative Knowledge Acquisition (CCoKA) model in figure 4.

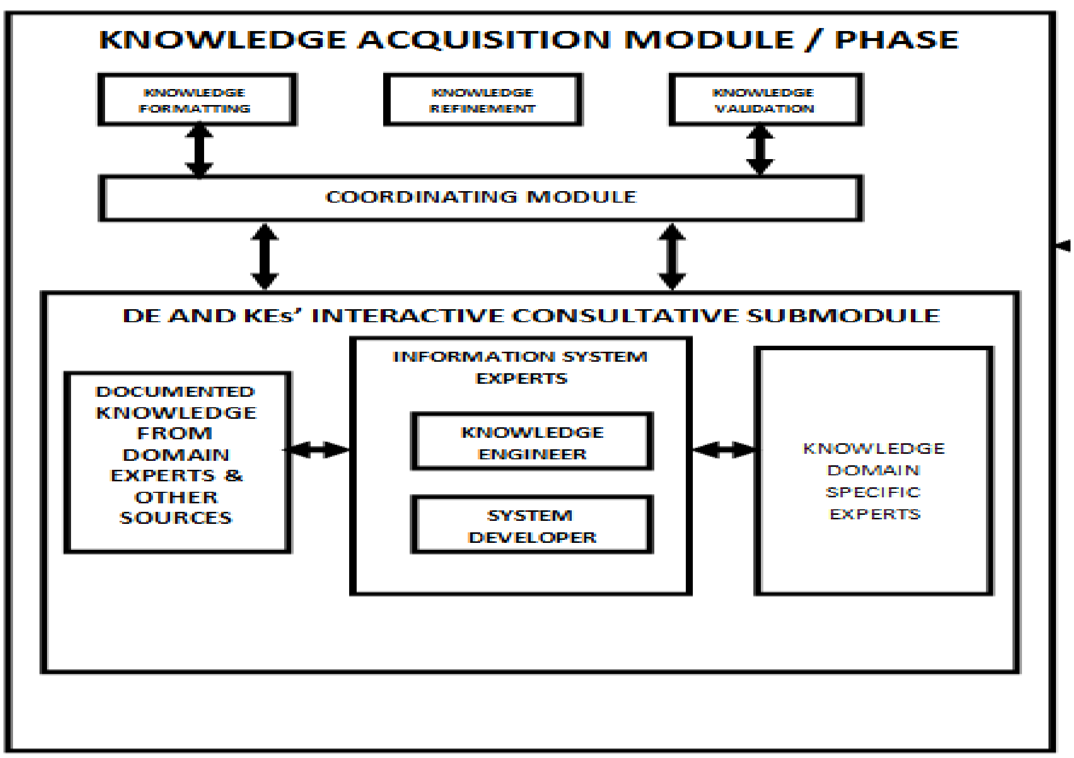

Figure 4: Consultative Collaborative Knowledge Acquisition (CCoKA) model for Knowledge Engineering AI Products Development
DE: Domain Experts
KE: Knowledge Engineers

4.0 Results and Discussion

CCoKA model's applicability was tested with Agricultural Extension Service Agents, Pathologists and other knowledge domain experts in Cocoa Research Institute of Nigeria (CRIN) Ibadan. The knowledge Engineer successfully used the Consultative Collaborative Knowledge Acquisition model's approach to convince, secure trust and elicit essential domain knowledge on problems affecting cocoa crops in Africa and the acquire appropriate treatments for these from domain experts from CRIN. Consequently, a Web Based Cocoa Health Expert System, WEBCHES with a dedicated website for the treatment of cocoa diseases was developed with the support and cooperation of these domain experts whose expertise proved useful in validating the product and its continuous updates. Figures 5 to 8 below show the results of the several modules of WEBCHES after it was implemented. The modules include:

1. The Landing or Home page module
2. The Extension Service Agents' Registration Page module
3. The Extension Service Agents' Login page module
4. The Farmers Search and View Result Page module
5. The Farmers' Pest and Diseases Details Page with Referrals module
6. The Extension Service Agents' Dashboard Page module
7. The Extension Service Agents View and Edit Pest or Disease Page module
8. The Extension Service Agents Add Pest or Disease Page module

The Home Page (figure 5) gives simple introductory information and links to both prospective and registered users (farmers and the extension service agents). The home page is also the landing page. From the home page, users can navigate to all other page.

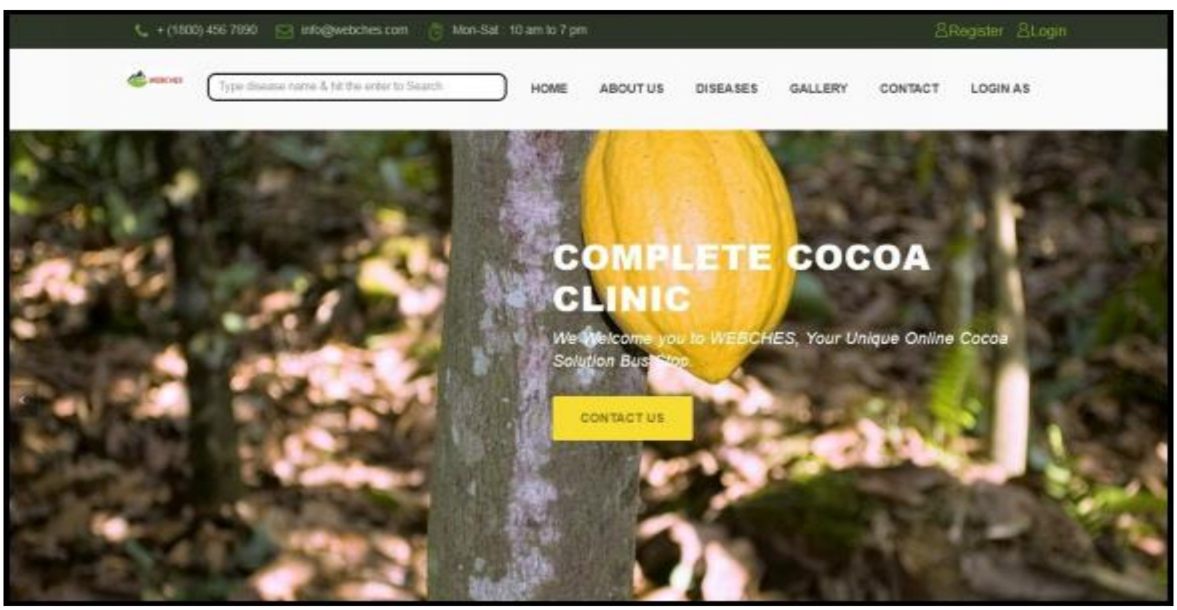

Figure 5: The Home Page

The LOGIN Page (figure 6) enables registered users to log in while prospective users are given opportunity to register. To log in users must supply their correct username and password. Prospective users have to register first by supplying their details to the system as requested.

The REGISTRATION Page (figure 7) contains the registration form. It offers the prospective user the opportunity to register by supplying his details into a registration form and submitting it for processing. After a successful registration, a prospective user will be granted access to allowed resources of the website.

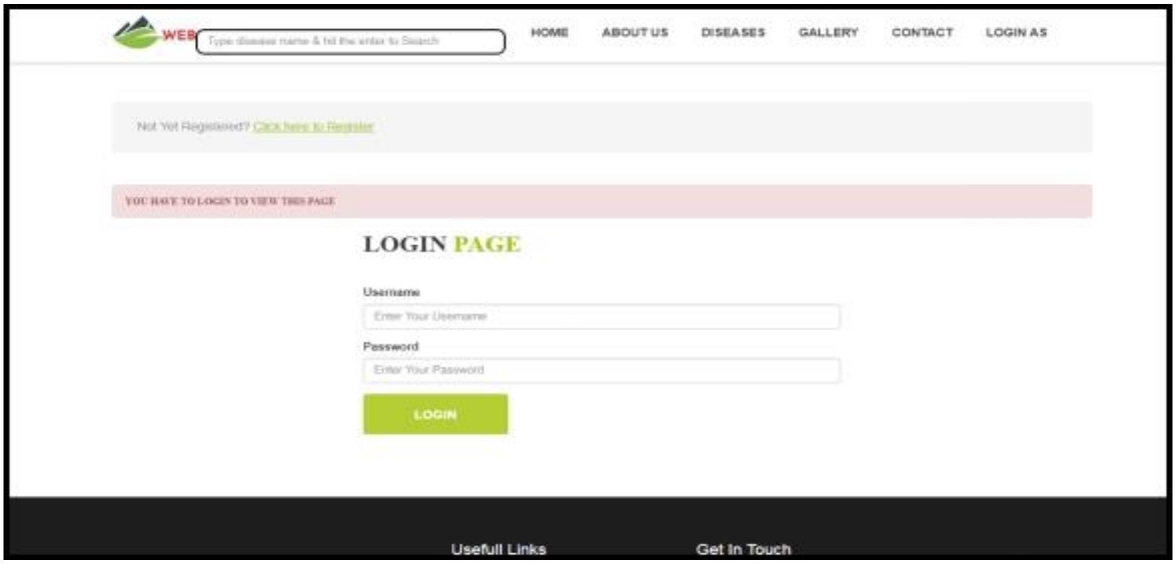

Figure 6: User's LOGIN Page

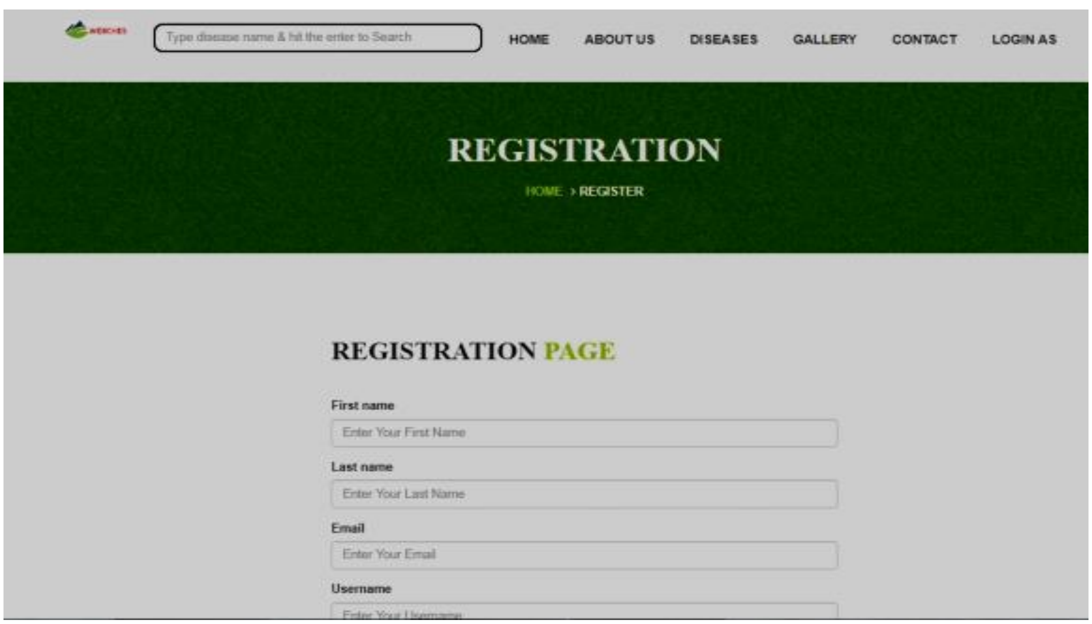

Figure 7: Users' Registration Page and Form

The farmers Search Page (figure 8) is the landing page for all the farmers that have clicked the link to access the farmers' page. This page consist of a search box, list of common cocoa pests and diseases, pagination to ensure more user interaction with the system and links in form of iconic images for the farmers to read more on the search results

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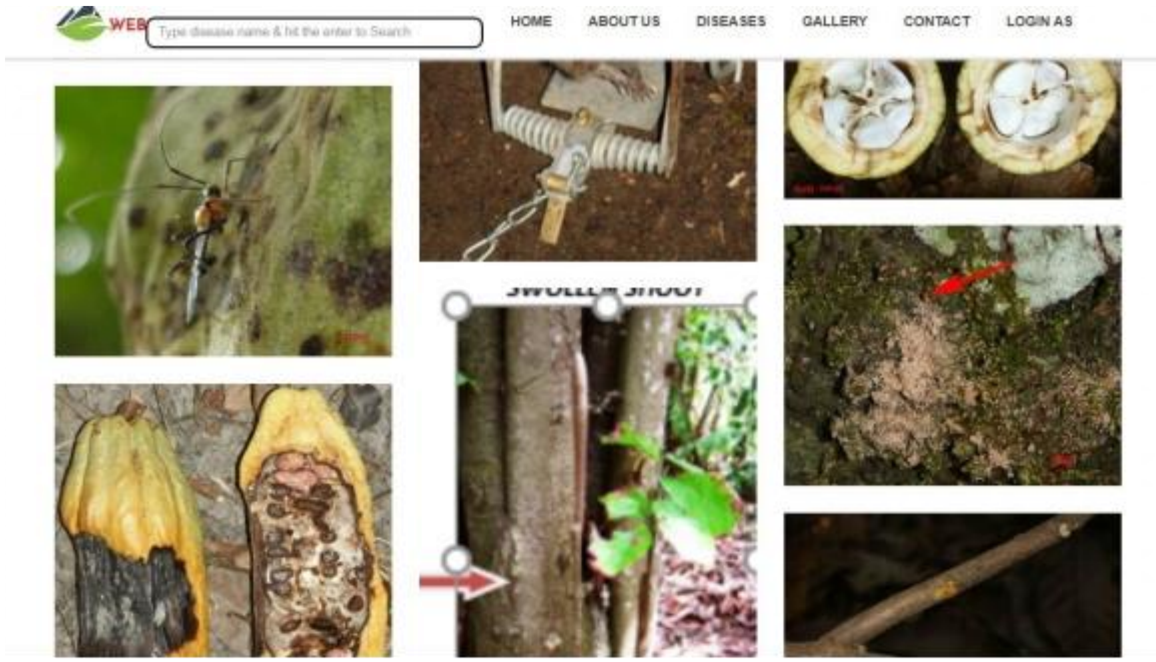

Figure 8: Search Page

The farmers' All Disease or Gallery Search Page (figure 9) at a glance provides the users with the list and images of all cocoa diseases and pests available in the website without details. Users are thus guided to select and concentrate on the challenge they want solution to. In case the problem is not listed, users' time is not wasted on fruitless searching and enhances efficient use of the processor and users' time.

The Pest and Disease Details Page (figure 4.6) provides users with the details information about the particular disease or pest selected from Gallery Search Page or from the farmers landing page. This detail can include disease/pest name (biological name in some cases), description, image of the pest, effect of its attack or image of infected tree, pod, leaves and or stem. It also includes prescriptive recommendation as an intervention to manage the problem. For further information, each disease or problem has a **READ MORE** referrals link (URL - Uniform Resources Locator to other sites like "http://www.icco.com") for the farmers to read more from other websites.

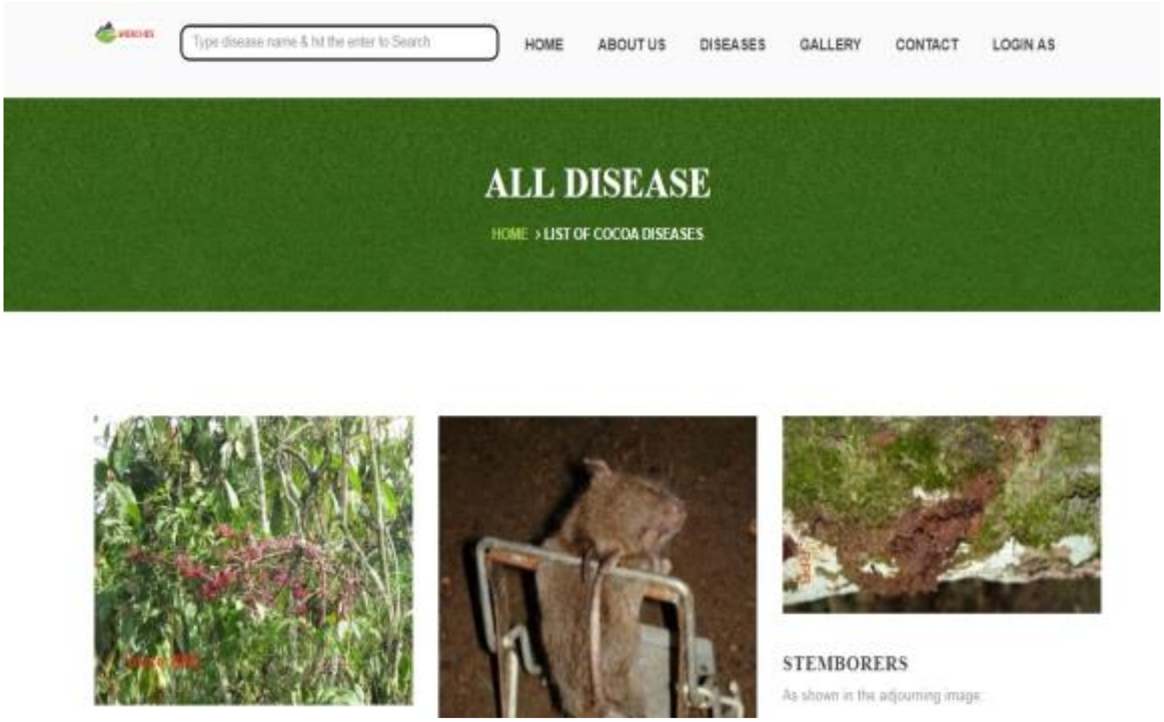

Figure 9: Farmers All Disease / Gallery Search Page

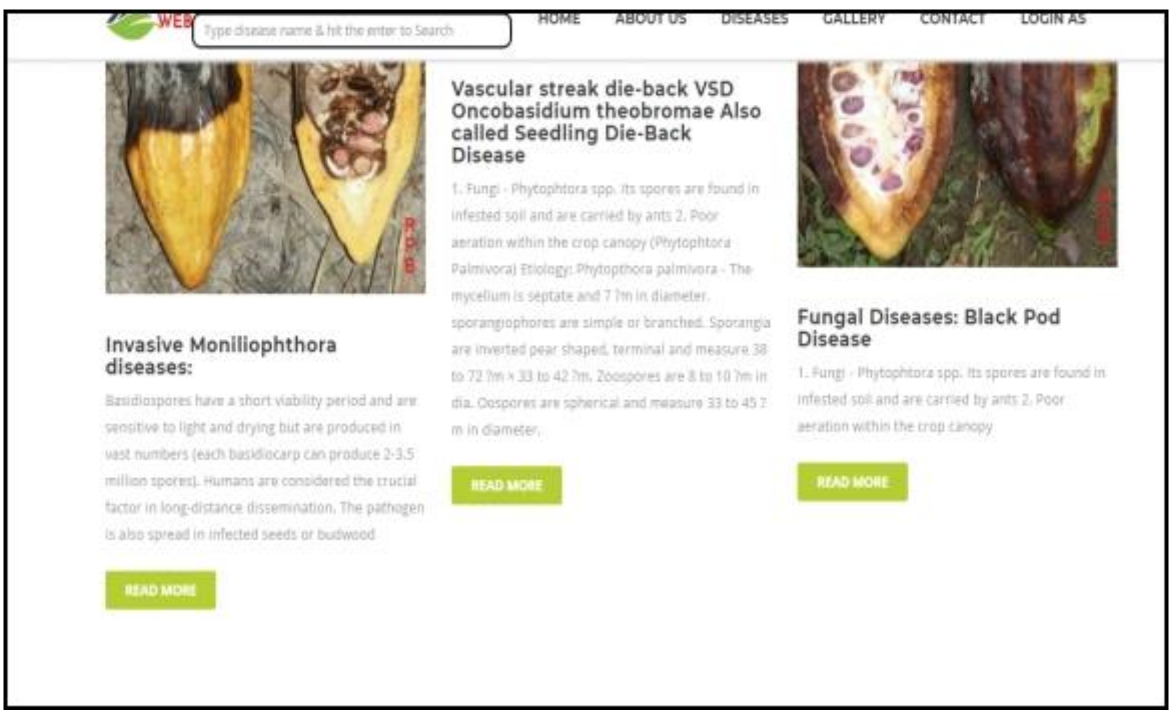

Figure 10: Pest or Diseases Details Page

After a successful login, the Extension Service Agent's (ESA) Dashboard Page (figure 11) offers the ESA his landing page. The page consists of Dashboard, Profile, Add Disease, Disease List, Contact and Logout pages. The ESA can check for disease list at Disease List page. If need be, he goes to The Extension Service Agent's Upload or Add Pest or Disease Page (figure 4.8). Here, the ESA or Knowledge Provider can specify the name of the new disease, its symptoms and remedial steps or medication to be submitted or uploaded to the System for redundancy check. If it survives redundancy check, it will be forwarded into a placeholder for System Admin's attention and eventual upload and knowledge base update. ESA can update his personal profile at Profile page (figure 12.

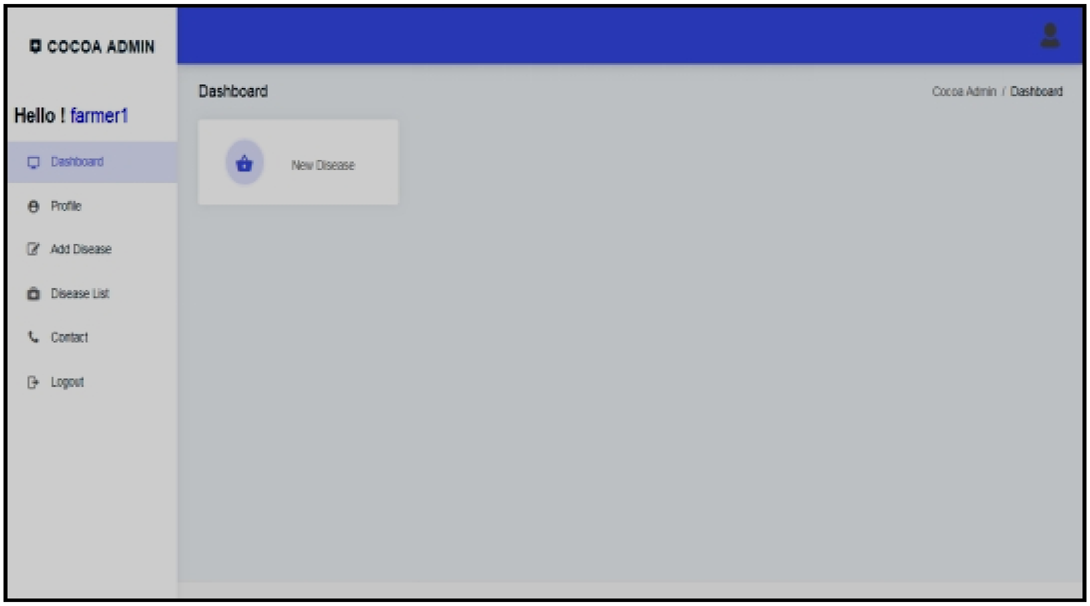

Figure 11: Extension Service Agent's Dashboard Page

Whenever there are newly discovered symptoms or remedies for an already existing disease or pest, an ESA can also use his Add Pest or Disease page (figure 12) to supply information to the system and the System Admin for redundancy check and ratification respectively before using it to update the knowledge base.

Figure 12: Extension Service Agent's Add Pest or Disease Page

Whenever there are newly discovered symptoms or remedies for an already existing disease or pest, as new updates waiting in the System Admin's placeholders queue, the System Administrator will be notified of this in The System Admin Update Pest or Disease Page (figure 13). He reviews the content and notify the trusted domain expert(s), whose recommendation might result in his clicking on **update** button to activate the autonomous update procedure or otherwise.

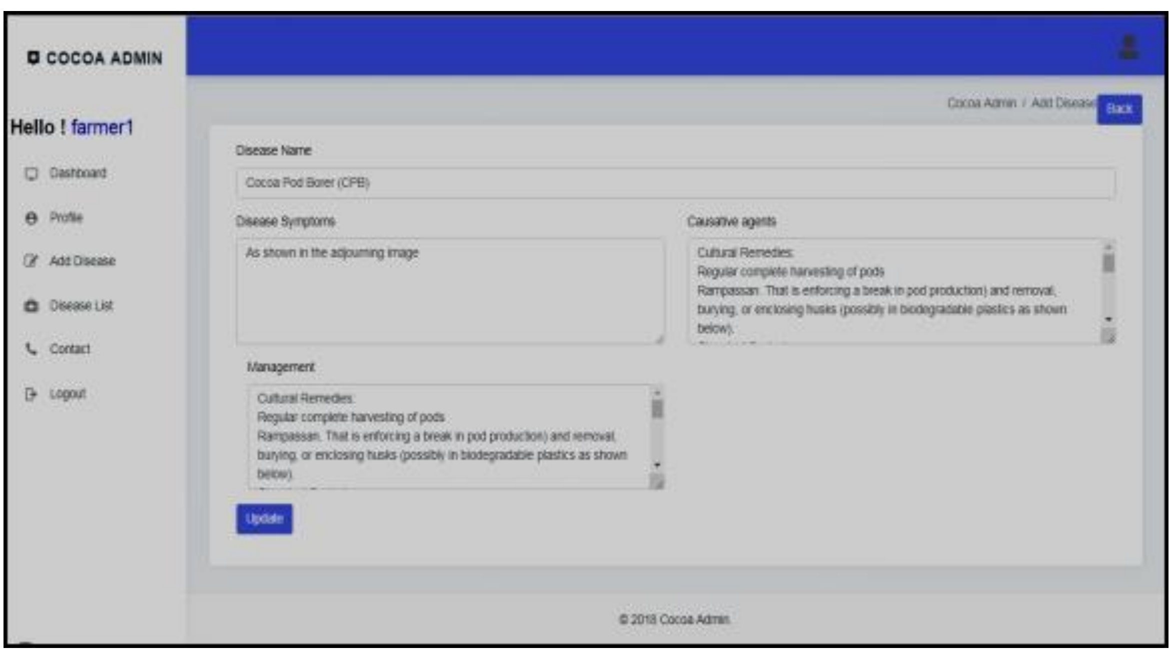

Figure 13: The System Admin Update Pest or Disease Page

It is apparent that without gaining the trust of the domain experts at Cocoa Research institute of Nigeria CRIN, made possible by applying the knowledge elicitation approach advocated in CCoKA model, the WEBCHES Expert system project and product will not have been successful. This is because the cooperation, support and continuous assistance of these domain experts (pathologists, Extension service agents etc) are mandatory to creation and populating the knowledge base of the expert system as well as maintaining it with up-to-date domain expert knowledge.

The same feat can be achieved in other specialized knowledge domains by adopting CCoKA model as a panacea to domain knowledge acquisition, validation and update challenges facing Knowledge Engineering (KE) in general.

5.0 Conclusion

In this study, a model - Collaborative Consultative Knowledge Acquisition (CCoKA) model was developed for overcoming the unique and persistent problem of knowledge elicitation from domain experts, prevalent and limiting performance in Expert System development and in Knowledge Engineering fields in general. The model was successfully adopted in eliciting domain expert knowledge needed for developing and web based Expert System WEBCHES for Cocoa disease management.

6.0 Recommendations

The researcher therefore recommends adopting CCoKA model in other knowledge domains for expert knowledge elicitation in Knowledge Engineering and expand further the horizon of Intelligent Computing and Artificial Intelligence in general.

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