DEVELOPMENT OF A HYBRID MODEL FOR ENHANCING DATA INTEGRATION PROCESS OF BUSINESS INTELLIGENCE SYSTEM

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Abstract:
Business Intelligence (BI) is predicated in helping people in management and experts to make accurate decisions using relevant information at the right time. It can also help to make more accurate forecast and strategies for organisations' business growth; data integration process that can handle very huge data (the big data phenomenon). The paper presents a hybrid model of two data integration techniques with case-based reasoning (CBR) as intelligent technique. It was developed with Java Script, Hypertext Pre-Processor (PhP), and My Structured Query Language (MySQL) programming languages using object-oriented analysis and design methodology (OOADM). The system was tested with disease control procedure in health sector industry in order to show the benefit of enhancing the data integration process in Business Intelligence systems. The results showed that the hybrid model of ontology-based data integration (OBDI) and virtual data integration (VDI) techniques had a higher enhanced BI process performance of 95% as against 75%and 65% for OBDI and VDI respectively. This shows that the hybrid model provided a better accuracy in predicting the disease control procedure, as it outperformed the existing model with 20% performance level.

Keywords: Data Integration, OBDI, VDI, Intelligent Technique, Case-Based Reasoning, Hybrid Model

1.0. Introduction

History of the concept of Business Intelligence (BI) dates back to 1958, when it was mentioned in an article authored by Luhn (1958). The term is said to be *a set of processes, know-how, methodologies, practices, applications and technologies whose goal is to effectively and efficiently endorse management activities and make timely and optimized business decisions* (Gartner, 2016; Novotný et al., 2005). The goal is to present business information in a fast, simple and efficient way. Business Intelligence (BI) support analytical, planning and decision-making activities at all levels and in all areas of corporate governance, enabling the viewing of reality from many possible angles (Ing. Dita Přikrylová, Brno, 2016) Again, Delic and Stanier, (2016), in Aneesha and Balajkarthik, (2017) noted that BI is the set of strategies, processes, applications, data, products, technologies and technical architectures which are used to support the collection, analysis, presentation and dissemination of business information.

BI process takes cyclical nature and includes stages of information needs, definition, information collecting, information processing, analysis, information dissemination, information utilization and feedback. The cycle is justified as the received feedback helps to re-evaluate or re-define information needs. In Business Intelligence (BI) process, there's usually no clear concentration on a specific topic or problem. The resources of a Business Intelligence (BI) system are used for constant monitoring of internal and external business environment (Rimvydas et al., 2013). It enables organization to obtain faster and easier access to information, to improve business processes and decision making as well as to identify the opportunities and the threats, while cooperating with customers, suppliers and competitors (Henrike et al., 2010). BI systems combine both data and analytical tools to present complex and competitive information to decision makers. It helps to improve the quality of inputs in the decision-making process, and knowledge management by making the best use of information (Aneesha and Balajkarthik, 2017).

The concept of BI is a management philosophy and tool that help organisations to manage and refine business information in order to make effective and intelligent decisions. It is used in relation to information and knowledge of organisation that describes the business environment, organisation itself, market conditions, customers, competitors and economic issues. It also, relates to a systemic and systematic processes by which organisations obtain, analyse and distribute the information for making decisions about business operations (Saeed et al., 2012). The objective is to perform its findings speedily and efficiently taking advantage of novel procedures which utilizes the inherent capabilities of finding electronic devices. The difficulty of finding relationships in the information provided, often results in improper decision, wrong actions, in action or duplication. Business Intelligence system objectives are to identify related interests by use of profiles of action points for (individuals' management, groups, departments, divisions or large unit). The major necessary function of Business Intelligence system is information retrieval (Dong-Hym and Ki-Ju, 2000). Figure 1.0 shows a generic Business Intelligence model.

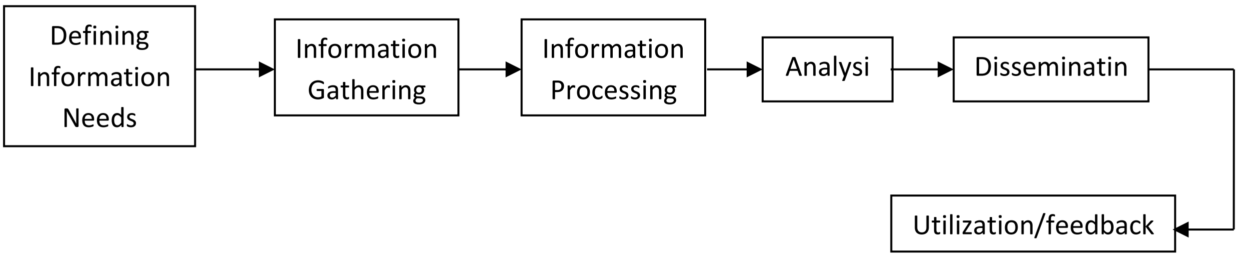

Figure 1.0: A Generic Business Intelligence Process Model (Source: Rimvydas et al., 2013)

In other words, BI systems serve common information needs of keeping users informed about the state of business environment, suggest intelligent solutions to experts of industries and often combines monitoring functions with alerts, exception reports as well as other tools to draw attention to changes or inconsistencies. Therefore, an important feature of BI system is their ability to produce a complete composite view that would help in avoiding surprises (Rimvydas et al., 2013).

Data integration is a key process in BI that involves many areas with respect to how it works. This may include ensuring the quality of the information being stored or making sure that data being transformed can be accessed within a reporting application in the most efficient way. The simplest form of data integration, for BI is the Extract, Transform and Load (ETL) which implies information is extracted from a data source like the Enterprise Resource Planning (ERP); packaged software to help organisations run the transactional side of their business, or Customer Resource Management (CRM) application etc. These data once extracted, transformations would occur such that when it is loaded within the data warehouse, it will be within a format that reflects the analytics required. Also, Extract Load Transform (ELT) is another form of data integration; where, instead of the transformations happening before being loaded into a data warehouse, they occur afterwards.

Case-based reasoning (CBR) as intelligent technique means using old experiences to understand and solve new problems. In CBR a reasoner remembers a previous situation similar to the current one and uses that to solve the new problem. CBR can mean adapting old solutions to meet new demands; using old cases to explain new situations; using old cases to critique new solutions; or reasoning from precedents to interpret a new situation (much like lawyers do) or create an equitable solution to a new problem (much like labour mediators do) (Kolodner, 1992). This was used to boost the intelligence of the enhanced BI process.
In summary, data integration (DI) is a fundamental, yet deceptively challenging, component of any organization's BI and data warehouse (DW) strategy. BI involves combining data residing in different data repositories and providing business users with a unified view of the data.

2.0. Related Literatures

With ontology, data integration has the task of providing a common view for users to access data, regardless of its actual organization and location as well as resolving the issue of interoperability which has to do with the problem of bringing together heterogeneous and distributed computer systems. Also, ontology-based data integration (OBDI) helps to resolve semantics conflicts which occur whenever two contexts do not use the same interpretation of the information. Semantic interoperability implies the ability to integrate data sources developed using different vocabularies and different perspectives on data and to achieve this, systems must be able to exchange data in such a way that the precise meaning of the data is readily accessible and the data can be translated by any system into a form that it understands (Hema and Chandramathi, 2013).

Ontology-based data integration (OBDI) is a system that provides a conceptual view on top of pre-existing information sources. Here, ontologies are used for the identification and association of semantically corresponding information concepts of data sources (Shokoh, 2009). There are three directions to data integration approaches using ontology: single ontology approaches, multiple ontology approaches, and hybrid approaches.

Kavassalts (2015) noted that the benefits of ontology-based solution is that it is more dynamic because it can be used as a basis for other applications and it has strong reliability and integration strength that provides a better and efficient way of information sharing. It can also act as a building block where it is reused in formalizing new concepts, as a support where it can play a supporting role in the development of new concepts, as a case where other conceptualizations can be derived from it, and as generic design that enables different applications to extract information whenever they need.
Shokoh (2009) observed that in the virtual data integration technique, the sources contain the real data and one or several virtual view(s) contain reconciled integrated schemas over these sources. The autonomous and heterogeneous data sources are queried by these homogeneous views. The query evaluation method depends on the mapping approach that the virtual data

integration system chooses. Carlo (2009) also noted that the traditional data warehouse (DW) forms yet another data silo in an organization, which leads to a slow degradation of the data warehouse benefits of providing optimized, integrated data delivery. Data Virtualization is used to create virtualized and integrated views of data in memory (rather than executing data moment and physically storing integrated views in a target data structure). Data virtualization (DV) enables a more agile approach to data integration (DI). Helena and Paulo (2015) reported that virtual data integration (VDI) technique when used in BI systems makes the architectures simpler, more affordable, and more agile. It reduces the need for data replication, improving data consistency as well as reducing the risk of introducing data errors and it focuses on time-to market business agility.

Further research on the concept of virtual data integration (data virtualization) can be found in Amineh et al, (2008) A RDF- based data integration, Magali and Michel (2005) Virtualization in System Biology: Meta Model and Modeling Language for semantic data integration, Laljo (2013) Data Virtualization in Business Intelligence, among others.

A third approach to data integration process in BI is the development of a hybrid of a materialized and virtual data integration approaches since both respond to different priorities. In a fully materialized approach, the main priority is the query response time, and in fully virtual data integration, data freshness is more important. However, in many data integration scenarios different priorities may be associated with different data and a trade-off between query response time and data freshness may be preferred to satisfying only one of these two issues. Shokoh (2009) opined that flexible approach which permits some data to be materialized and other data to be virtual can satisfy both of these goals. In the existing hybrid approaches the global view is partitioned into materialized and virtual parts. Some objects or relations are chosen to be materialized and others reside in the local sources and will be extracted at query time.

Wooldridge (2009) noted that intelligent agent technology is a new paradigm suitable for developing system that situates and operates in a dynamic and heterogeneous environment. Its architecture is considered as the functional brain of an agent in making decision and reasoning to solve problem and achieve goals. He referred to an agent as an autonomous software entity that is situated in some environment where it can monitor and response to changes proactively or reactively or adaptively by itself or through communication with other agents to persistently achieve certain goal or task on behalf of user or other agents.

Gavin and Zhaohao (2003) again noted that CBR systems are a particular type of analogical reasoning system which have a diversity of applications in many fields, such as in intelligent Web based sales service and Web-based planning as well as in multi-agent systems. With CBR as an intelligent process in the research for enhancing of the data integration process of BI just as in intelligent or multi-agent system, its goal is to infer a solution for a current problem description in the domain from solutions of previously solved problems, termed the case base or case memory. This CBR concept is widely used for the definition of the needs for the design and development of expert and intelligent systems (Paul-Eric, 2011).

BI and health sector analytics are emerging technologies that provide analytical capability to help health sector industry improve service quality, reduce cost and manage risks effectively. But these integrating and intelligence components on analytical health sector data processing are largely not included in the current health sector information technology (Tobias and Vivian, 2008). The role of BI technology in health sector cannot be over emphasized, because the sector has vast mass of data to explore to its advantage using BI. These vast amounts of data that is now being generated and captured in a variety of formats and from a number of disparate sources is what is today referred to as Big Data. In order for these data to be analysed so as to bring about actionable information, advanced BI tools for analytics, such as data mining, predictive analytics, statistics, and artificial intelligence (AI), are now being explored and implemented in big data analytics. These unending streams of data generated in the health sector every day, is unconditionally important that it can be collected, filtered, controlled and then reused for patient care, teaching or for research purpose (Mihaela and Manole, 2015).

Furthermore, real-time information accessibility would enable frontline managers and health sector leaders to make informed evidence-based, intelligent and accurate decisions about management priorities in areas of resource allocation, patient flow, patient treatment and diagnosis as well as quality management (Loewen, 2017).
In summary the review of literature discussed the key concepts for the design and implementation of the hybrid model for enhancing data integration process in BI system, which would be tested on disease control procedure aspect in health sector.

3.0. Methodology

The research focused on patient care, whereby the executives (physicians/doctors) use the new model to take decision on prescriptions accuracy and on-time treatment for patient care and decision on disease control prevention as well as prediction. The disadvantage of not using this analytic feature is the inability of not making use of all available data, since the ability to manage such vast amount of data is getting difficult and stressful. Also, even when used (that is the analytics feature of BI and Big Data), some still miss new insights, thereby not being able to imagine the potential of the vast amount of data. Figure 3.0 describes the use of a registry in a health sector setting that is not fully automated. It shows the flow of information from the point of patient's visit till a physician has attended to the patient. The process is not fully automated as some of the computerization makes use of a stand-alone disease registry at care point.

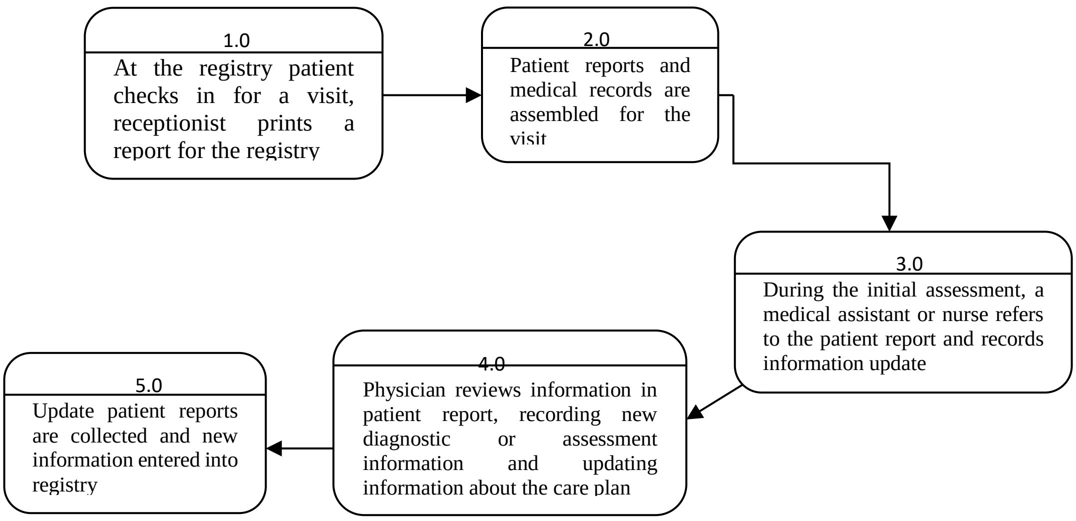

Figure 3.0 Existing System Process

In the model, ontology is used for describing semantic meaning of information source explicitly in order to solve semantic heterogeneity. Generally, database schemas are regarded as static, but ontology schemas are typically assumed to be highly dynamic and are an evolving object(s). The ontological model was presented in a modular fashion, which is divided into the following sections: diseases (age group and gender); symptoms with anatomy, intensity and evolution, and risk factors. A diagnosis must be an instance of the disease concept and it is governed by the Catalogue of Disease. Therefore, three sub-ontology(s) are created that shape the complete model: Diseases, Symptoms and Risk Factors. Figure 3.1 shows the complete model of the ontology and their relationships between sub-ontology.

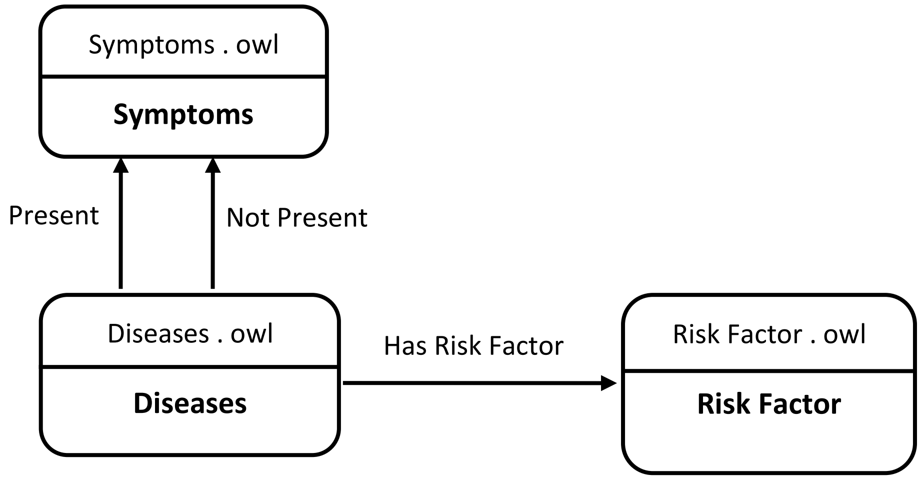

Figure 3.1 Ontology Model Using Web-Ontology Language (OWL)

Data virtualization (VDI) layer enables views with high performance and it integrates optimizations into the query engine that do not violate any underlying semantic constraints. A comprehensive DV solution provides a deeper level of knowledge about the structure, formats, and the semantics associated with the data sources. The major difference between a comprehensive DV framework and the simplistic layering of access and caching services via data federation is that the comprehensive DV solution goes beyond just data federation. It is not only about heterogeneity and latency, but must incorporate the methodologies that are standardized within the business process to ensure semantic consistency for the business. Figure 3.2 show the virtualization layer framework.

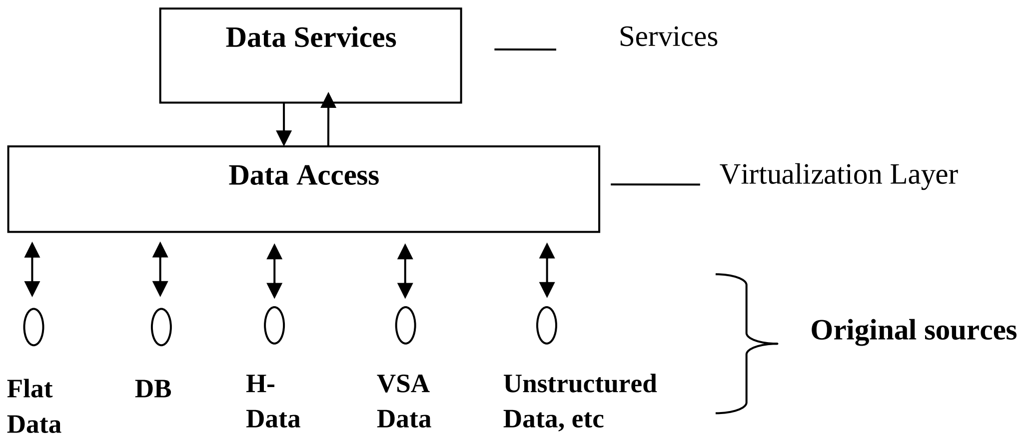

Figure 3.2 Layers in a Data Virtualization Framework

In summary, figure 3.2 is the generic sample framework for a BI database system. Its main goal is to establish an environment for the decision makers in various levels of business organisations and enterprises such that they can acquire or generate knowledge from the bulk of heterogeneous data sources, create their hypothesis and then make intelligent reliable decision for the positive progress of their business establishment.

4.0. System Design and Implementation

In building a data integration (DI) system, a uniform query interface and schema are presented. It involves abstracting away multitude of sources and consults them for relevant data when the need arises. It unifies different sources autonomously that are initially not designed to be integrated (Helena and Paulo, 2015).

The ontology architecture for data integration (DI) is three; single, multiple and hybrid approach. The ontology is created using either of resource description framework (RDF), resource description framework schema (RDFS), DARPA mark-up language (DAML), ontology interchange layer (OIL), and/or web ontology language (OWL). But OWL is more powerful than others; OWL has a well-defined semantics and highly optimized implementation system compared to the others. Figure 4.0 and 4.1 shows the architecture of ontology-based data integration (OBDI) and virtual data integration (VDI) respectively.

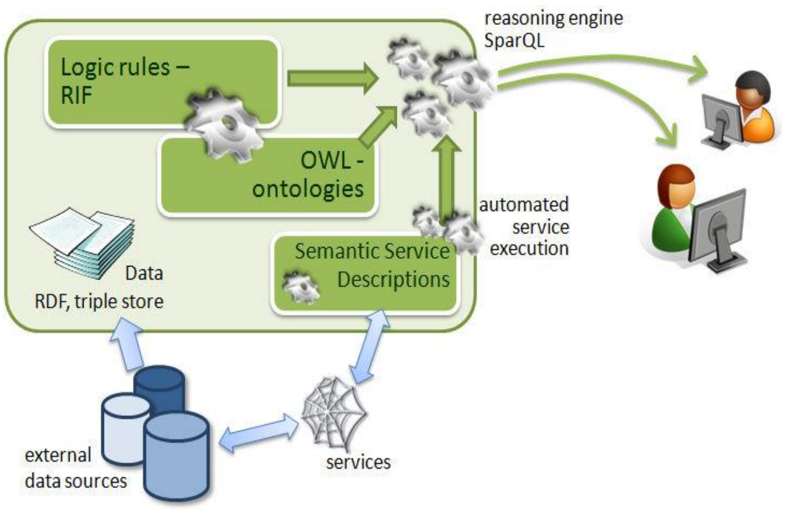

Figure 4.0 Ontology-based Data Integration Architecture (Source: Bostjan and Vili, 2010)

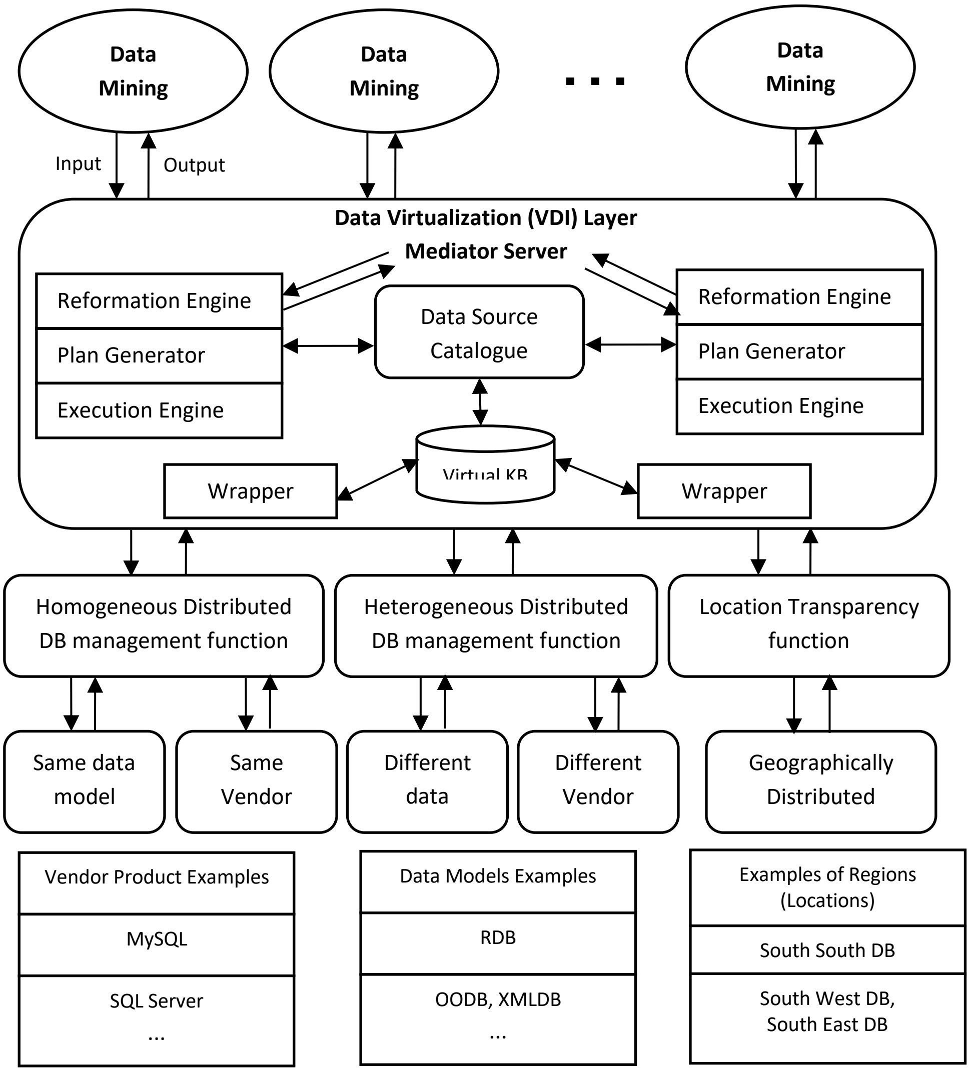

Figure 4.1 Data Virtualization (VDI) Technique of the Model

In order to be used for data integration (DI), virtual data integration (Data Virtualization) platform must do data cleansing; data transformation and data correlation. Data warehouse (DW) does each of these stages separately and produce physically transformed data at each stage. Unlike data warehouse (DW) and extract transform load (ETL), data virtualization (DV) platform would do all of these stages mostly in one step of producing the final reform. Data Virtualization platform needs to define data cleansing, data transformation and data correlation logic programmatically using structured query language (SQL) like query language.
Case-based reasoning, broadly construed, is the process of solving new problems based on the solutions of similar past problems. An auto mechanic who fixes an engine by recalling another car that exhibited similar symptoms is using case-based reasoning. Figure 4.2 shows the sample architecture of a case-based reasoning (CBR) intelligent agent.

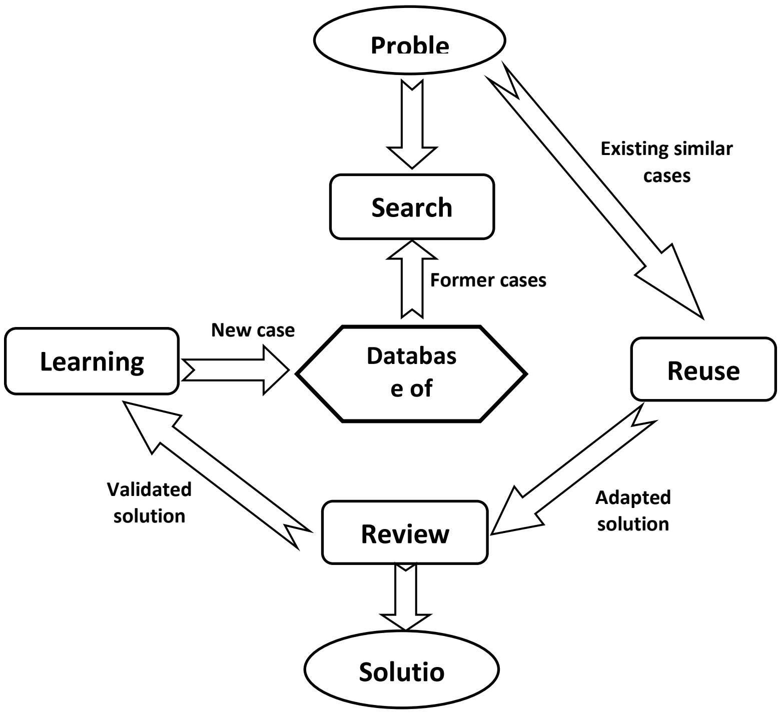

Figure 4.2 Architecture of Case-Based Reasoning (CBR) Technique

The architecture of the new system model is tagged HMEBIP (a hybrid model for enhanced Business Intelligence process). The aspect of the Business Intelligence process the research is enhancing is the data integration phase. This is enhanced with the hybrid of two data integration techniques; ontology-based data integration (OBDI) and virtual data integration (VDI). Also used is the case-based reasoning (CBR) intelligent process technique in enhancing the intelligence of the system. Figure 4.3 shows the architecture of the enhanced developed new model.

The process flow of the system is boosted with an intelligent technique as indicated in the data integration layer of the architecture of the system design. The data integration layer is where the ontology-based and virtual data integration process takes place and it is the aspect of the business intelligence process that the research is enhancing. Figure 4.4 shows the system flowchart process of the hybrid of both data integration techniques (OBDI and VDI).

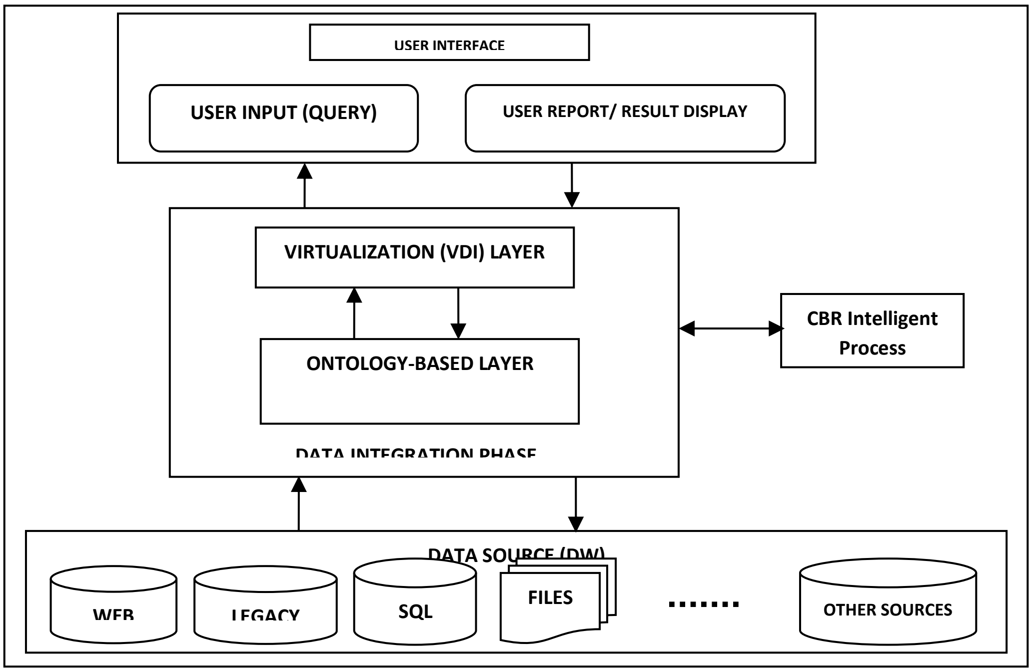

Figure 4.3 Architecture of the New Model (HMEBIP)

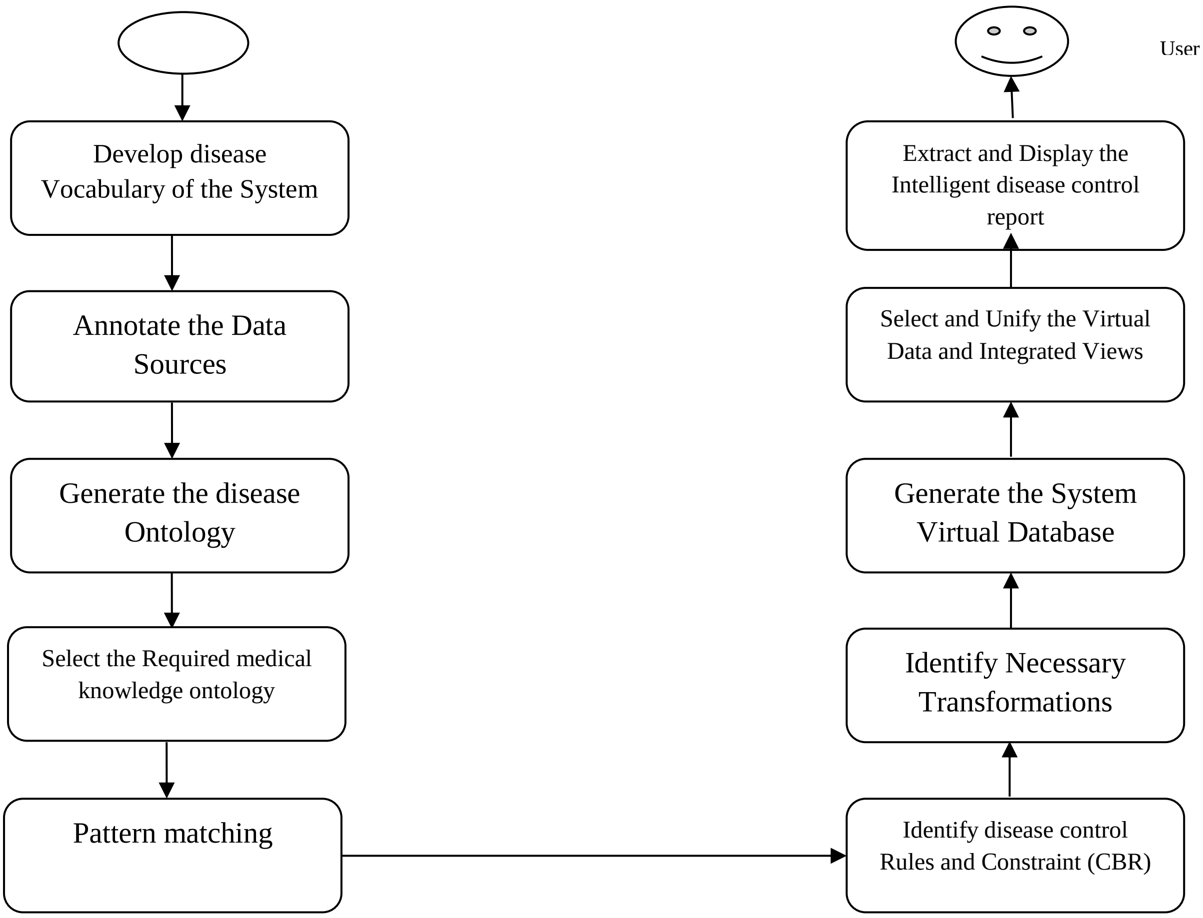

Figure 4.4 Hybrid Process of the new model

5.0 Findings, Results and Discussions

A comparison test of the hybrid model for data integration process in Business Intelligence and each of the single models of either ontology-based or virtual data integration techniques was carried out. Figure 5.0 shows the graphical presentation of the findings, while figures 5.1 and 5.2 indicate the sample results after implementation of the designed software.

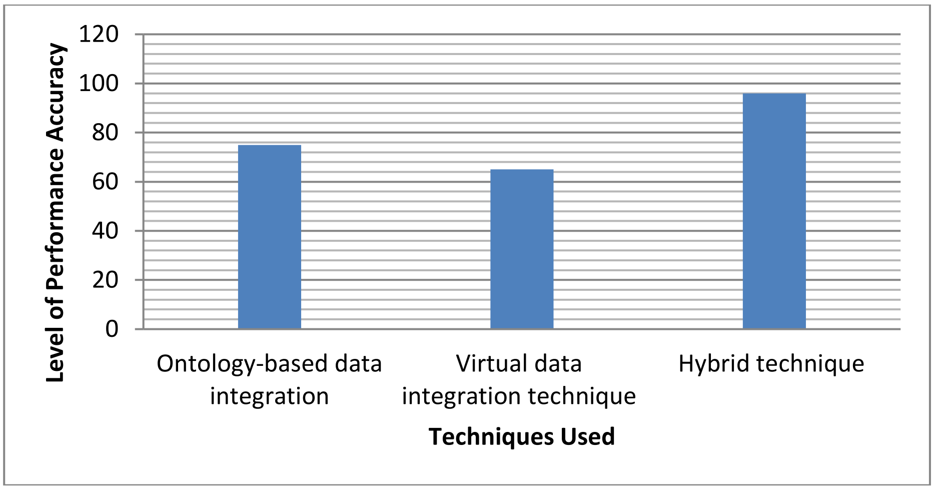

Figure 5.0 Comparison of level of prediction accuracy using various techniques

And from figure 5.0, it can be deduced that the Ontology-based data integration technique for disease control procedure has 75% accuracy in predicting the disease control procedure; Virtual data integration technique for disease control procedure has 65% accuracy in predicting the disease control procedure; while Hybrid technique using both Ontology-based data integration and virtual data integration technique for disease control procedure has 95% accuracy in predicting the disease control procedure. This shows that the Hybrid technique outperforms the existing techniques with (95 – 75) equals 20%, i.e. there is 20% improvement from the existing technique. Figures 5.1 and 5.2 show the sample software output.

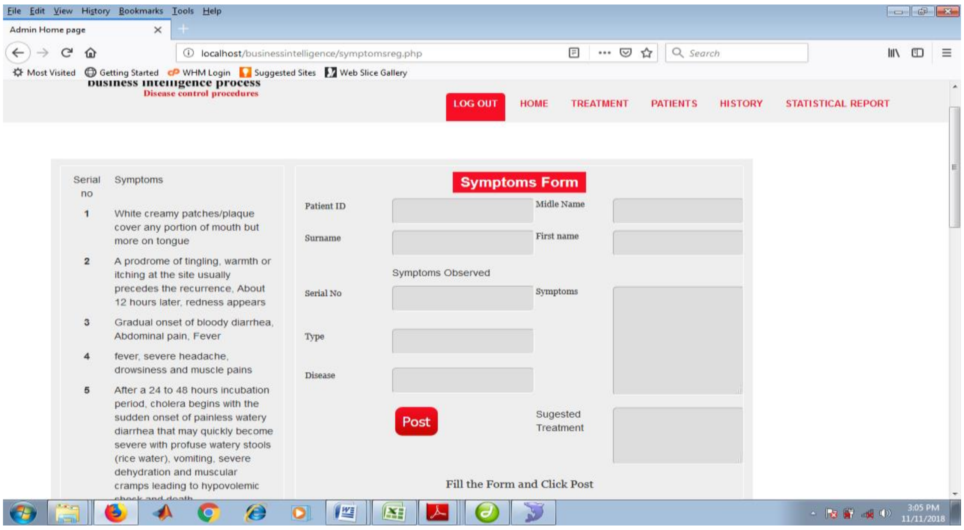

Figure 5.1 Disease Ontology Form

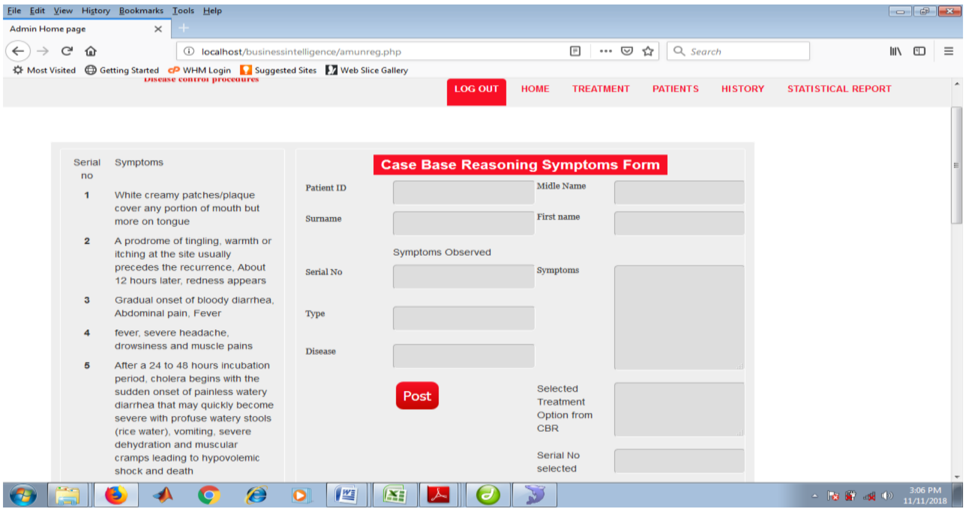

Figure 5.2 Case based reasoning / data virtualization form

Limitations of the System

In the test running of the new system, where there is existence of a lot of treatment procedure for a given disease, the system selects one out of the recommended treatment and it may turn out not to be the best out of all options as the age difference of the patients involved may be a barrier for maximum efficiency of the treatment procedure. This is one of the limitations of the developed system.

6.0. Conclusion and Recommendation

Business Intelligence (BI) is intended to enable business users to easily access and analyze relevant enterprise information so that they can make timely and facts-based knowledge decisions. The ontology-based data integration (OBDI) process model solves the problem of heterogeneity in Business Intelligence (BI) data integration process, which makes the BI system to be adaptive, intelligent, automatic, and user-friendly. While the virtual data integration (VDI) process model that has to do with data virtualization which brings about speed and agility to accessing data in the Business Intelligence (BI) system. The hybrid model of both techniques; ontology-based data integration (OBDI) and virtual data integration (VDI) in a Business Intelligence (BI) data integration process eliminates the cost of purchasing BI system to solve heterogeneity problem separately and any other to solve the speed and agility problem differently.

In developing nations like Nigeria, data are rarely collected and stored at a single entry point especially in the health sector. Integration from multiple heterogeneous sources is a prerequisite step for many applications, e.g., decision aids, data/information fusion and data mining. It is also a prevailing task by many organizations in order to improve their knowledge sharing as well as the efficiency of their operations. This can be of immense benefit to physicians who are in need of these vast amounts of knowledge for their daily life saving operations.

Utilizing ontology-based data integration and virtual data integration is an attractive avenue as it is also a key factor for enabling interoperability. However, integrating vast amount of information/data from different heterogeneous sources is a difficult, complex and demanding task. The combination of ontology-based data integration and virtual data integration techniques to automate the data integration process in a Business

Intelligence task has reduced the time and effort in making better prediction as shown by this work.

The hybridization of other approaches to data integration for Business Intelligence system in other domain sectors is recommended to be carried out using other types of intelligent techniques so as to determine the effectiveness and benefits of hybrid models. Also, it is recommended that all health sectors in Nigeria should integrate the model developed in the research into their electronic patient records so as to help doctors in accurately carrying out disease control procedures. Finally, government should encourage the medical practitioners by providing the necessary funds to implement an automation of this magnitude. This would help to improve the health sector performance and as a result restore hope to the Nigerian health system.

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