Development of an Integrated Medical Intelligence System for Clinical Decision Support

[1]Eze Irene Ifechi and [2]Ogochukwu Okeke
[1]Department of Computer Science, Federal College of Education (Technical) Umunze, Anambra state, Nigeria
[2]Department of Computer Science, Chukwuemeka Odimegwu Ojukwu University, Anambra State, Nigeria
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Abstract

The of aim of this paper is to develop an integrated medical intelligence system for clinical decision support. The medical system in Nigeria today suffers from lack of fast, accurate, reliable and intelligent software solutions that can help healthcare practitioners make decisions that would solve urgent, and in some cases, complex medical problems in real-time. Also, the cost of processing and analyzing large volumes of data in a medical environment is high most especially in terms of time consumption. So, this thesis proposed a patient-oriented design for integration of large volumes of data in order to improve database validity compared to procedure-oriented design that multiplies the redundancy of data. The research addressed the problems, by having a hybrid of ontologies and virtual data integration in order to enhance medical intelligence process. A hybrid model for enhance medical intelligence process using ontology based and virtual data integration technique was developed. The design provided for a database system for storing medical records, software for enhanced Medical Intelligence Process that would be more user-friendly, flexible, adaptive, intelligent, agile and automatic in integrating and analyzing medical data thereby helping medical practitioners at various levels to make realistic intelligent and real-time decision on critical health issues. Object Oriented Analysis and Design Methodology (OOADM) were adopted in the design of the system

Keywords: *Health System, OOADM, Virtual data Integration, Intelligence process*

INTRODUCTION

In a healthcare system, a lot of data is generated on daily basis and it is becoming more data driven than ever before. Healthcare is an evidence-based practice and requires information to be utilized quickly and effectively to improve patient outcomes. In the health sector, patient's data are scattered in different hospitals and resides in different database. Collecting or integrating these data together is a big challenge for clinicians, health service managers, and researchers who routinely obtain and process data from an array of sources. Also, the representation of the data gathered is of concern as wrong representation of data can mislead the clinicians). Advancement in information technology have enabled vast amounts of digital health data to be collected and analyzed. There exist what we called electronic medical records which hold clinical records of patients in datasets and also health systems that monitor people with long-term conditions and stores the observations in a datasets. These datasets can be looked as big data as vast amount of data is involved. Ways of representing the data in a more meaningful and graphical form is being sort for, hence the need for data analytic and visualization in healthcare sector. Medical intelligence is the ability to detect and cure an ailment on time with minimal effort. It requires vast knowledge on disease symptoms, cure, and this can only be achieved by having a data warehouse build from the knowledge of medical experts. To apply medical intelligence effectively, the healthcare condition of the patients must be ascertained. The health-care condition of a patient is defined as all the past and current medical and social information about the patient that may affect the professional immediate and short term management of that patient (Chih-Lin, 2019). In this thesis, this information corresponds to all the diseases, syndromes and social issues that are diagnosed for the patient, the signs and symptoms (including family medical history), the problem assessments performed (i.e., medical, social, cognitive, and mobility tests), and the current interventions, either pharmacological, rehabilitative, nurse care, social care, counseling, and special medical services. Ontologies are one of the most successful ways of representing actionable knowledge in bio medicine (Rosse, 2019). Two of the reasons for this success are their ability to capture biomedical knowledge in a formal but simple, powerful and incremental manner, and their easy application in the reasoning processes performed by medical decision support systems (Ouwens, 2015).In health care, the most common, complex and resource-consuming clinical cases to deal with correspond to chronically ill patients, who are a kind of patients that deserve long term and simultaneous assistance provided by several sorts of professionals, as for example family doctors, specialists, nurses, or social workers. In order to deal with this highly variable kind of patients, we need mechanisms to personalize the knowledge describing both the condition of these patients (each individual patient is a potential different case with specific diseases, syndromes, social needs, signs and symptoms), and the intervention plan for these patients (the actions to be followed for different patients are eventually very varied). But we also need mechanisms to assess whether the decisions and recommendations on these patients are correct or not in part because the possibilities of over- and under-treat these kinds of patients can be very high. Also, integration becomes a crucial challenge as heterogeneous data is generated by various healthcare systems. This has to do with how to integrate various types of data including patient demographics and environmental data, clinical monitoring systems, pathology and radiology imaging data, textual data from clinical reports etc. Bianchi et al. (2019) describe the integration of clinical, environmental and genetic data and point out with examples how ontologies are used to normalize data from various disparate systems.

Review of Related Works

Natural Language Processing for Smart Healthcare

Smart healthcare is a healthcare system that exploits emerging technologies, such as artificial intelligence (AI), block chain, big data, cloud/edge computing, and the internet of things (IOT), for realizing various intelligent systems to connect healthcare participants and promote the quality of healthcare (Tian, 2019). Major participants in smart healthcare can be classified into three categories, i.e., the public, healthcare service providers, and third-party healthcare participants. Related to the participants, representative smart healthcare scenarios include smart homes, smart hospitals, intelligent research and development for life science, health management, public health, rehabilitation therapy, and etc. Figure 1 shows the major participants, emerging technologies, and representative scenarios of smart healthcare.

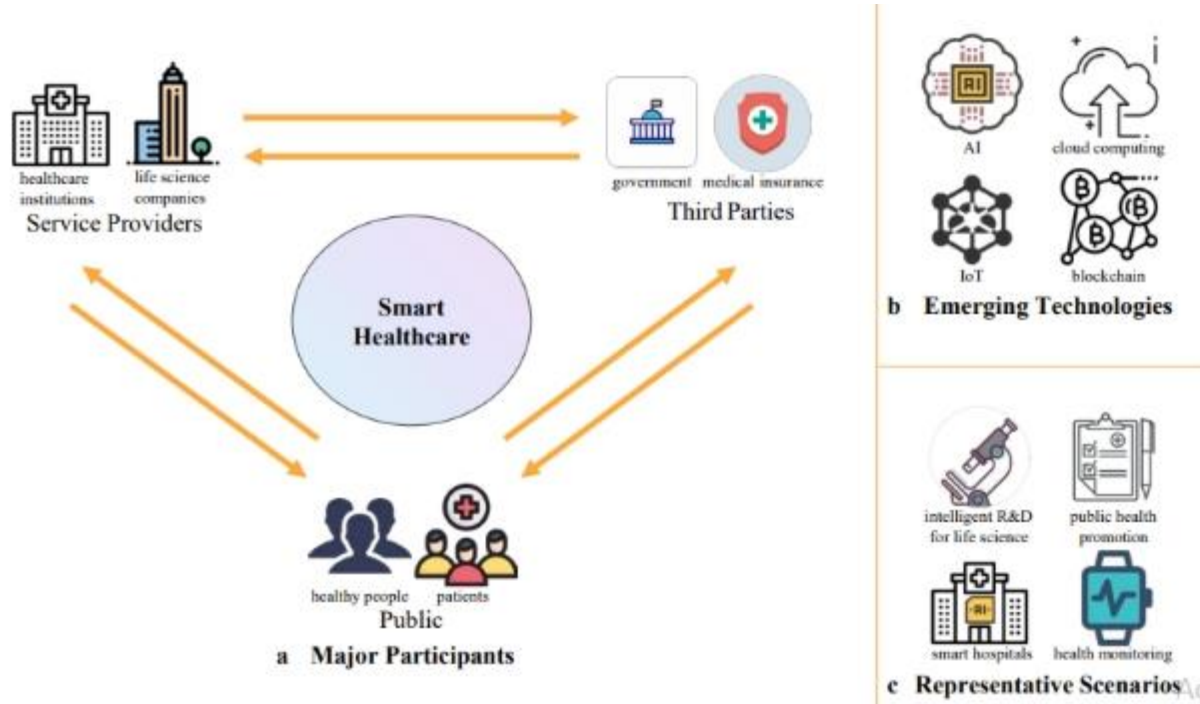

Figure 1: Smart healthcare (Tian, 2019)

Figure 1a is the major participants in smart healthcare include the public, healthcare service providers, and third-party healthcare participants. Figure 1b is example emerging technologies enable smart healthcare applications include artificial intelligence, block chain, cloud computing, the internet of things, and etc. figure 1c is representative smart healthcare scenarios include intelligent research and development for life science, public health promotion, smart hospitals, health monitoring, and etc. Natural language processing (NLP) is a sub field of computer science and artificial intelligence that is concerned with the automatic analysis, representation and understanding of human language (Young, 2018). NLP has become a hot research area and has attracted widespread attention from many research communities in the past several years. As human language is a general form of data entry for intelligent systems, NLP enables machines to understand human language and interact with humans, making it essential to smart healthcare. The main manifestations of natural language are text and speech, where text encompasses text records, articles, book chapters, dictionaries, and so forth, while speech occurs in human-human and human-machine dialogues. NLP has been developed for several decades following the early origin of artificial intelligence in the 1950s. Approaches to conduct NLP are generally divided into three categories: rule-based approaches, statistical approaches, and deep learning-based approaches (Young, 2018). From the 1950s to 1980s, NLP research mainly focused on rule-based approaches, which required expertise in both computer science and linguistics to design rules that fit human language. However, even well-designed rules are quite limited for covering human language due to its flexibility and complex patterns. Since the 1980s, statistical NLP systems have been designed by extracting features from corpora using statistical and machine learning algorithms and have gradually replaced rule-based NLP systems due to their superiority in performance and robustness. With the early application of the neural probabilistic language model (Bengio, 2013) and the rapid development of deep learning since 2013, neural NLP, by using neural networks and large corpora for automated feature learning, has dominated current research and achieved SOTA performance of many NLP tasks (Young, 2018). In smart healthcare, NLP is applied to process text data and is associated with human-machine/human-human communication. The text data can be classified into 2 categories: clinical text and other text data (Young, 2018). Clinical text comes from all clinical scenarios and mainly comprises of unstructured text records from electronic health record (EHR) systems, including medical notes, diagnostic reports, electronic prescriptions, and etc. Other text data include all text that appears within other healthcare scenarios, e.g., surveys in population screening and articles for evidence-based reference. Communication is common in all smart healthcare scenarios, such as patient-provider communication in clinical inquiry and human-robot interaction in rehabilitation therapy, accompanied by applications such as machine translations and user interfaces for rehabilitation robots. (Madhura, 2020) titled "A data integration platform for patient-centered e-healthcare and clinical decision support", the researchers proposed an open data integration platform for patient, clinical, medical and historical data across multiple health information systems. As an open platform, it can accommodate and integrate further heterogeneous data sources such as data streams generated by wearable Internet of Things (IoT) devices. As an integration platform, it facilitates centralization of data assets. This centralization empowers every stakeholder in a patient-centered care setting to actively participate in decision-making. A range of analytics and reporting solutions, such as data warehouse, interactive dashboards, and predictive analytics tools, can be deployed upon this open data integration platform. The proposed platform is currently being adapted and implemented to address patient-centered healthcare and clinical decision support requirements in a sports injury clinic at a not-for-profit private hospital in Melbourne, Australia. Use Case based demonstration of the platform's suitability for holistic information management, decision-support, and predictive analytics justify its role in the advancement of e-healthcare. The research suggested than advanced analytics, data visualization, monitoring and reporting functionalities for clinical decision support will should be added and customized in future work and this is identified as the research gap. Medical decision support systems based on machine learning was presented by (Chih-Lin, 2019). The central idea of the dissertation is aimed at facilitating personal health care, reducing costs of health care, and improving outcomes. They proposed a new machine-learning algorithm for three disjointed health care problems: hospital referral, cost-effective diagnosis, and lifestyle recommendation. In the hospital referral and lifestyle recommendation projects, individualized recommendation is generated based on the input of personal characteristics and preferences. The systems can then return the best individual solution (hospital selection or the plan of lifestyle changes) that fits one's preference and personal considerations. In the cost-effective diagnosis project, the recommendation of a test is provided based on individual information (including symptoms and previous test results). The recommended test has the highest potential to cross (or get close to) the treatment (or non-treatment) threshold. In other words, they optimize diagnosis in terms of the number of tests and the amount of cost without sacrificing accuracy (sometimes improving accuracy). For the lifestyle project, the dataset is the description of a specific population. First, the recommended lifestyle is thus the best lifestyle observed from that population. Some known healthy behavior may not be recommended when most people do not have the behavior. For example, when most people consume saturated fat more than 7% energy (this cut-point is suggested by American Heart Association), the system may not recognize the benefit of satisfying this criterion. In addition, due to bias, the recommended lifestyle may not be the best for patients not in that population. Sozan (2019) presented a thesis titled "Intelligent System for Identification Heart Diseases" to the graduate school of applied sciences of near east university. In her submission, she said that most of existing traditional medical systems are based on the knowledge of experts-doctors. In her thesis, the application of soft computing elements is considered to automate the process of diagnosing diseases, in particularly diagnosing of a heart attack. The research work offers probable help to the medical practitioners and healthcare sector in making instantaneous resolution during the diagnosis of the diseases. The intelligent system predicts heart attacks from the patient dataset utilizing algorithms and help doctors in making diagnose of these illnesses. In the study, three techniques such as a neural network (back propagation), Fuzzy Inference System (FIS) and Adaptative Neuro-Fuzzy System (ANFIS) are considered for the design of the prediction system. The systems are designed using data sets. The data sets contain 1319 samples that include 8 input attributes and one output. The output refers presence of a heart attack in the patient. For comparative analysis, the simulation results of the ANFIS model are compared with the simulation results of the neural network-based prediction model. The ANFIS model has shown better performance and outperformed NN based model. The obtained simulation results demonstrate the efficiency of using ANFIS model in the identification of heart attacks. Serdar (2018) presented an "Intelligent Systems in Patient Monitoring and Therapy Management". The research pointed out that although today's advanced biomedical technology provides unsurpassed power in diagnosis, monitoring, and treatment, interpretation of vast streams of information generated by this technology often poses excessive demands on the cognitive skills of health-care personnel. In addition, storage, reduction, retrieval, processing, and presentation of information are significant challenges. These problems are most severe in critical care environments such as intensive care units (ICUs) and operating room (ORs) where many events are life-threatening and thus require immediate attention and the implementation of definitive corrective actions. The article focuses on intelligent monitoring and control (IMC), or the use of artificial intelligence (AI) techniques to alleviate some of the common information management problems encountered in health-care environments. The article presents the findings of a survey of over 30 IMC projects. A major finding of the survey is that although significant advances have been made in introducing AI technology in critical care, successful examples of fielded systems are still few and far between. Widespread acceptance of these systems in critical care environments depends on a number of factors, including fruitful collaborations between clinicians and computer scientists, emphasis on evaluation studies, and easy access to clinical information. Vishesh, 2017 titled "Personal health record system (PHRS) and integration techniques with various electronic medical record systems", the researcher proposed a Web-based PHRS that can store data in a cloud-based architecture. The proposed system is web based and is built on J2EE technology which will enable users to access and share the medical health information from any place at any time with desired care provider. Integration of healthcare information systems is a complicated task and full of challenges. To effectively handle the large volume of medical imaging data system uses the open-source system. The cloud computing based architecture was used which allows consumers to address the challenge of sharing medical data.PHRS provides a complete and accurate summary of the health and medical history of an individual by gathering data from many sources. This makes information accessible online to anyone who has the necessary electronic credentials to view the information.

Method of Data Collection

Data were gathered as fellow:

1. Review: document about patient's medical record was reviewed for the purpose of updating knowledge. This is very essential as it involves direction and result achievement.
2. Observation: health infrastructures were observed, strategic locations of network that can enhance electronic services were also observed.
3. Interview: health stakeholders were interviewed to gather information on how to serve them better in public health care.

Analysis of the System

Medical record system allows users to register patients and have the record stored in a database. It also track patient's visits and generate a reminder for patient or physician of the needed follow-up. The typical workflow begins with the physician reviewing a patient's information from a computer terminal to view the information online. The physician can also retrieve patients list. Once a patient visits a clinic, his/her medical information will be recorded and stored in the database for future access. In electronic health record system environment especially where client's application and data is stored in a server system, users will interact with the server data sharing system through a server-client application. Server-client application is a front end service that performs most of the critical operations in the given architecture. Most of the data operations are performed only through server-client application, such as data storage and data retrieval. In retrieving the patient's data, the new system integrates data from different hospitals and health centers so as to enable physicians visualize the previous medical history of the patient. The interoperable healthcare system lies in the maximum usage of medical and health resources by integrating important medical technologies and sharing the medical resource and information.That includes three specific objectives as follows:

- The new digital medical service pattern and service process standard with the complete modern medical information system
- The integration of national healthcare sharing platform to achieve the unified procedure, and service sharing among medical institutes in certain area combined with the monitoring and evaluating system for the sharing services.
- Provision of services, such as two-way referral, online medical consultation, remote medical record and test result query,online medication consultation and patient‘s following-visit,in the community and hospitals of intermediate and advanced level.

The above mentioned objectives demand a sophisticated information structure that features the following four core requirements:

- The integration of existing information systems of the medical institutions in the country for the capability of medical resource sharing.
- The integration platform of medical institutions for public information service to government, medical organization, community and citizen on disease control.
- The data center of medical information in the hospitals as the main data source for the integration platform realizing the medical information sharing.

Since the information of healthcare domain is diversified and dynamic because of the heterogeneous and distributed information resources and the large amount of daily updated data produced by many information systems from medical institution, the key problem for constructing integrated healthcare system is the efficient management of medical workflow and the effective integration of mass data resources. In the system, the healthcare centers are responsible for the medical data from each healthcare data center to monitor patient records. Each information integration platform is composed of hospital, clinics and community healthcare center by which different levels of medical institutions are able to share the data from data centers and realize two-way referral and medical record lending. The information sharing among different medical systems not only needs to provide full accessibility to the data but also requires the interoperability among these systems. The main problems caused by bringing together heterogeneous and distributed computer systems are summarized as semantic heterogeneity and structural heterogeneity. Semantic heterogeneity refers to the variation of semantic meaning in medical information resources which will lead to the semantic conflicts and complication for data integration. Structural heterogeneity means that the same data will be described in different structures by different systems because of various application systems, DBMS and operating systems. In this new medical intelligence system, we will take advantage of ontologies for the explication of medical knowledge as a possible approach to overcome the problem of semantic heterogeneity and the problem of structure heterogeneity will be solved by the use of XML based data integration together with data warehouse. In the realm of knowledge management, ontology provides both the theoretical basis and the applied methods to morph the different knowledge modalities to form a unified knowledge object since they can be used for the identification and association of semantically corresponding information concepts.In the healthcare sharing platform, ontologies are used for describing semantic meaning of information source explicitly in order to solve semantic heterogeneity. In effect, the proposed ontology-based and virtual data integration architectural process would be based on the use of ontology which explicitly captures knowledge about different types of data sources and virtual aspect uses mediators to bring about the real-time and agility aspect of the system. Generally, database schema are regarded as static, but ontology schema are typically assumed to be highly dynamic and are an evolving object(s).
The proposed ontological model is presented in a modular fashion, which has been 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.

The proposed system will add the following features to the existing system

- Integration of data across various hospitals to aid in data sharing and decision making

- To provide support by integrating clinical guideline-based prompts into the patient report such as guideline based interval for assessment of test for diseases, interventions that are overdue for disease control and guidelines for medical care.
- More advanced rule-based prompting incorporates patient-specific information and is able to generate customized care recommendations such as treatment prescriptions, recommendation of next test because of patients health is falling short of the desired outcome.

We choose to use Web-Ontology Language **(**OWL) to describe ontology for its particular roles in information integration and because it relies on extensible markup language (XML) schema data types. Furthermore, based on the hybrid ontology approach, the semantic heterogeneity will be solved for information integration. The basic structure of medical information should provide the interface and logic to manipulate these data in a unified way based on the results of data integration. The service–oriented integration(SOI) combines the traditional integration object with open and highly flexible web services, and provides an abstract interface through which medical information systems can interact with each other instead of by bottom protocol and user-defined programming interface specifying how the system communicates with other systems. The medical information is described in the form of services so that other services can discover and select to interact and bind with them when they are running or being designed. The hospital data integration is based on Integrating the Healthcare Enterprise (IHE). The Cross-Enterprise Document Sharing (XDS) is proposed in IHE in order to solve the problem of medical information sharing. Based on the ontology method for heterogeneous information integration from semantic level, we also present a virtual database to realize the data integration. The main source of data in actual hospital institutions for integration is relational database. Comparing with ontology approach to solve the semantic heterogeneity, the XML based data integration of hospital information systems provides a unified interface of data manipulation for practical application to deal with structural heterogeneity. XML schema serves as the global data model and XQuery is the unified transformation language for operation of data source. The integration result is in the unified form of XML which can be shared by application programs and systems. Together with ontology for semantic integration, the XML based virtual database of hospital information system is composed of four parts: query processor, integration service manager, semantic part and structural part.

- The query processor manages the query request and control request respectively according to user’s data request and return the results in the form of XML
- The integration service manager manages the meta data, local view and global view of the data source for integration by the definition of integration task and cooperates with global ontology and query processor.
- The semantic part deal with the semantic heterogeneity by ontologies.This part gets the XML based source information from structural part and provides knowledge to integration service manager.
- The structural part concerns the structural heterogeneity .The Wrapper is responsible for interacting with low-level data source, packaging heterogeneous data source and operating the relational database using standard SQL with the aim of realizing the transparency of data location and visiting.

The data integration provides the basis for middle service layer by sharing the information. However the shared data must be transported to medical information systems in a proper way. The proposed system is suitable for the mass information exchange among hospitals, insurance company and super administrative departments. The proposed system will track patient's visits and will generate a reminder for patient or physician of the needed follow-up or preventive care against a discovered disease. The typical work flow begins with the physician reviewing a patient's information from a computer terminal to view the information online. The physician can also retrieve patients list with similar disease. The richer the medical registry's data set, the greater the possibilities for examining subgroups of patients with related cases and how it was treated. The registries include standard reports and permit user to query the system for specific date ranges and interventions or patient status indicator. In the proposed system, physicians can use the patient's information to develop a strategy for treatment of each patient. It can allow the physician to contact the patient via SMS to advice the patient on the need to come for follow up or take certain medication. During this process, physician become aware of problems with registry information such as finding that the patient is no longer coming for treatment or has changed health service provider. The disease registry can generate report with different views of aggregating information about the process or outcome of health care management. It can show the population of patients suffering from a particular disease, the number treated successfully, and a feedback to physicians about the status of their patients, and the possible treatment to apply.

Data Flow Diagram (DFD) of the Proposed System

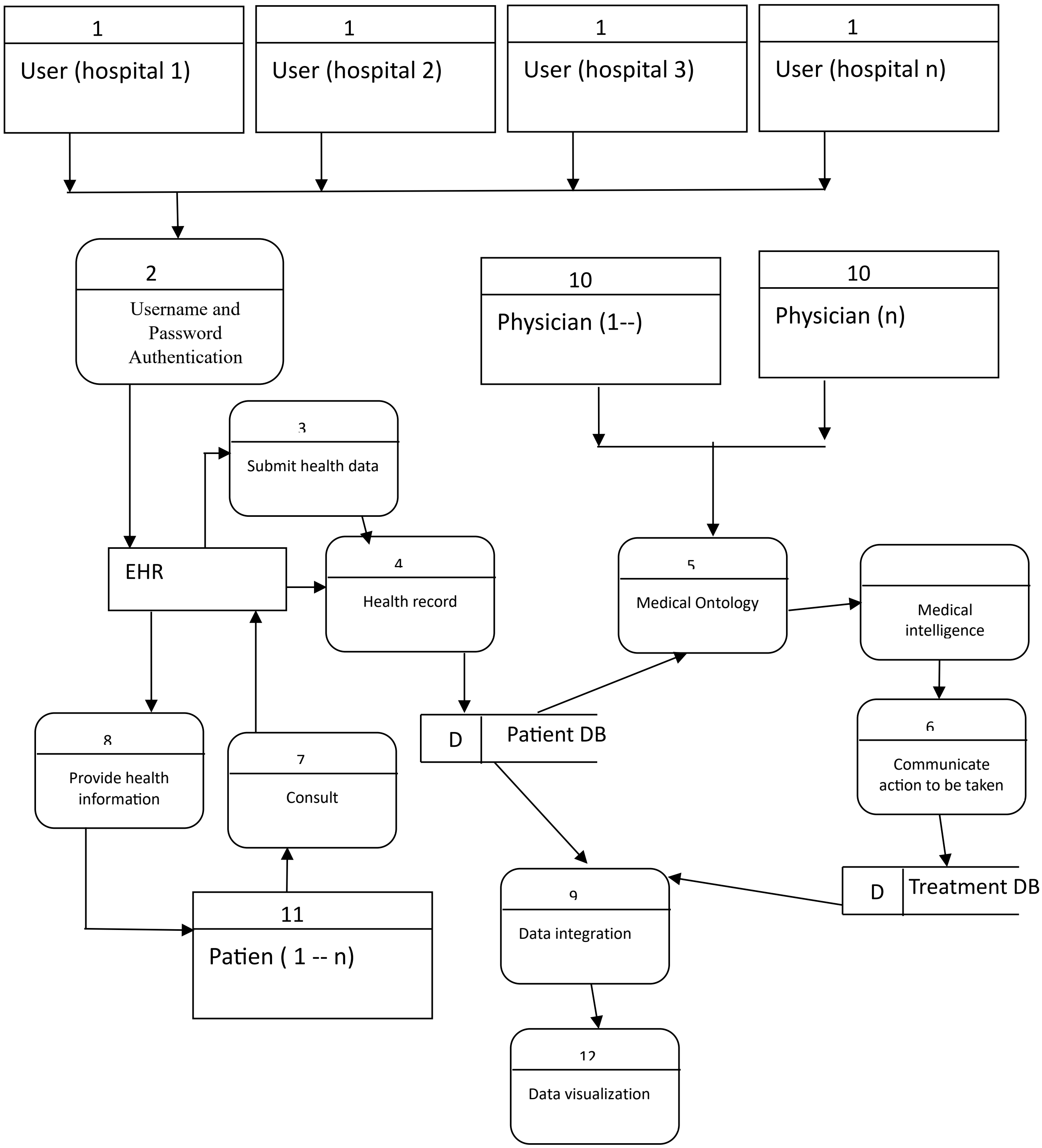

Figure 2: Data Flow of the System

As shown in figure 2, the health sector is responsible for the medical data from each regional data center. The information integration platform is composed of hospital, clinics and community healthcare center by which different levels of medical institutions in a region are able to share the data from data centers and realize two-way referral and medical record lending. Meanwhile different integrated information platforms can exchange the resource data and perform remote consultation.

Use Case Diagram

The model designed in this thesis is divided into several modules that needs access restrictions. Different use cases were described in the way they were applicable in the software designed. Use cases are as listed below.

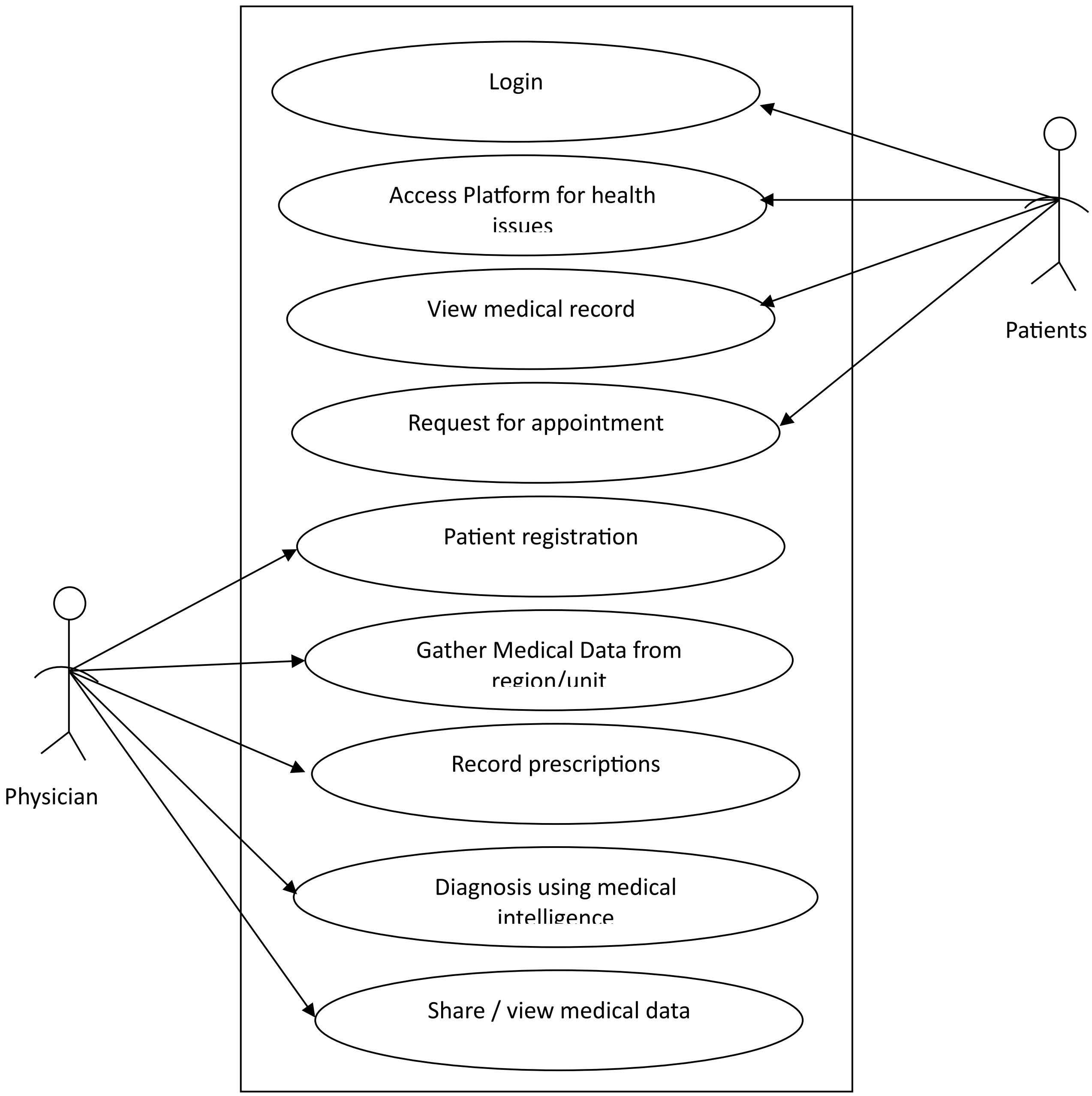

Fig.ure3: Use Case Diagram of the Proposed System

Result and Discussions

During the testing, 30 tests were carried out to see how it can accurately identify and classify the patient diseases based on the knowledge acquired from the dataset using medical intelligence. Table 1 shows the performance grading of the medical intelligence.

Table 1: **Confusion matrix applied to test dataset**

Observed

		True	**False**
	True	12	1
Predicted	**False**	0	17

Table 4.7 shows that out of 30 test conducted using medical intelligence, 12 are True Positive and were predicted correctly. 17 were detected to be True Negative and were predicted correctly. 1 was False Negative (shows the wrong classification) while it is not. Finally a model of performance metrics can be derived from the confusion matrix as show in equation 4.1, which shows the accuracy of the system.

Substituting the values we have

AC = (12+17) / (12+17+0+1)

AC = 0.967 i.e. 96.7% accuracy in predicting the outcome of the diagnosis (see table 2).

Table 2: **Performance Results Obtained**

Technique Applied	**Accuracy in classifying the symptoms**
Medical Intelligence	96.7%

Limitations of the System

In the test running of the new system, where their existing 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 forms the limitation of the proposed system.

Conclusion

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 from different sources is a difficult, complex and demanding task. The use of ontology-based data integration systems and virtual data integration tools to automate partly the data integration task and reduce this effort has been achieved in this paper. Advances in intelligent systems, e.g., "Intelligent Information Agents" for the Internet, will help doctors in accurately carrying out disease control procedures. Emerging and more mature standards such as "Extensible Markup Language" (XML), "Ontology Web Language" (OWL) and Web Services based on "Simple Object Access Protocol" (SOAP), "Universal, Description, Discovery, and Integration" (UDDI) and "Web Service Description Language" (WSDL), will also help to resolve many software-level interoperability problems. The application developed in this thesis relies on these Web interoperability standards in order to integrate information dynamically. Therefore the health sector will benefit very well from the system developed as it will integrate patients records across board making healthcare system better.

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